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THE ROLE OF OCCUPATION-SPECIFIC HUMAN CAPITAL IN ECONOMIC ANALYSIS

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ABSTRACT

THE ROLE OF OCCUPATION-SPECIFIC
HUMAN CAPITAL IN ECONOMIC ANALYSIS

By

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This three-chapter compilation examines the theoretical and empirical implications of occupation-specific human capital as it relates to current labor economics research. The first chapter demonstrates that acknowledging occupational specificity in the human capital model allows for a reconciliation of a long-standing theoretical dispute regarding the role of occupation in the labor market. The second chapter extends the literature by estimating the cross-occupation transferability of human capital using data on the knowledge, skills, and abilities utilized in each vocation. These estimates are then applied to verify displaced blue-collar manufacturing workers as structural "victims" given lower rates of human capital application in their new occupations compared to others displaced in the labor market. The third chapter investigates the relationship between high school employment and post-school economic outcomes, as it uses occupation-specific human capital principles to dismiss the notion that in-school employment provides the "marketable skills" necessary to stimulate post-school economic gains.

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OCCUPATION AND THE HUMAN CAPITAL MODEL

INTRODUCTION

With standard applications ranging from discrimination to education, the wage equation has evolved into the most fundamental analytical tool utilized by labor economists. With origins tracing back to Mincer (1974), its prevalence in the field is evidenced by the fact that no less than forty articles featured a wage equation in the *Journal of Labor Economics* between 2000 and 2004. However, despite the pervasiveness of its usage–and perhaps because of it–cross-sectional approaches are typically nonchalant in specifying occupation in the model, even absent data restrictions. For example, efforts to "include occupation" in a regression can run the gamut, ranging from a simple white-collar vs. blue-collar demarcation (Arai 2003) or a series of five occupational controls (Wheeler 2001) to expansive sets of controls, whether it be thirteen 13 vocational variables (Bratsberg, Ragan, and Nasir 2002) or other more sophisticated techniques (Hirsch and Macpherson 2004). This inconsistency has failed to be rigorously examined–or even denoted–in labor economics literature despite the fact that it plays a significant role in shaping research findings offered through the wage equation.

While this paper will investigate this issue, the inconsistency of occupational specification in the wage equation mirrors a larger, unresolved ambiguity in vocation's role in the human capital model, the underlying theory from which the wage equation was derived. Thus, while the human capital model envisioned by Mincer (1958) and Becker (1962) sparked the "human investment revolution in economic thought" (Bowman 1974) that serves as the foundation for much of today's labor market analysis, the failure of the model to predict certain occupational phenomena has fueled an undercurrent of dissent over the validity of the theory, which, in turn, has manifested itself in alternative research streams such as segmented labor markets (SLM) and sorting models. This dissension has been typically steeped in institutional thought, with supporting literature questioning the human capital model's theory of wage determination (Fogel 1979), explanation of educational wage premiums (Spence 1973), its neoclassical economic assumptions (Gottschalk 1978), and to some extent, its definition of the labor market itself (Osterman 1975; Kerr 1977). While debate over these issues reached its climax in the 1970s, the role of occupation in the model has never been resolved, as reflected in the adversarial relationship between human capital theorists and institutional scholars that exists to the present day (Budd 2005; Vedder and Gallaway 2005).

While scholars have typically recognized the concurrent influences of human capital and institutional thought at work in the labor market (Becker 1993), attempts to bridge the theoretical gap between the two schools have been minimal. However, a small, but recently revitalized literature on occupation-specific human capital may represent a simple elaboration of human capital principles upon which to establish a reconciliation of the occupation-based failings of the human capital model. Originally advanced by Shaw (1984), it has been only recently that scholars have begun to examine the implications associated with occupational specificity within the human capital framework (Milgrom 2004; Kambourov and Manovskii 2004a, 2004b, 2005; Sullivan 2005a, 2005b; Groen 2006). Given these confirmations of occupation-specific human capital's role in determining labor market outcomes, the opportunity now arises to revisit these occupation-based critiques of the human capital model to examine how this elaboration of the theory may harmonize the seemingly disparate arguments of institutionalists and human capital theorists.

To examine the questions surrounding occupation's role within the wage equation and, more broadly, the human capital model, this paper will begin by laying out the human capital theory and its suggestions for occupation's role. Next, this study will synthesize occupation-based critiques of the human capital model into a cohesive reference, an absence in the literature that may have been partly responsible for the inherent ambiguity surrounding vocation's place in the theory. Moving on, the next section of the paper will examine the evidence on occupation-specific human capital before laying out the bridges this refinement may provide between institutional and human capital thought. Finally, this paper will apply these lessons to examine the initial topic advanced by this paper–the specification of occupation in the wage equation.

LITERATURE REVIEW

Human Capital Model View of Occupation

In response to wage analyses of individual occupations, the original goal of the human capital model was to serve as a means through which researchers and practitioners could explore the economic impact of investing in people from a broader, more general perspective (Becker 1993, 29-30). While the founders of the model may have been apprehensive about dubbing their theory "human capital" (Becker 1993, 16), the theory recognizes that people, like factories and businesses, are entities that can be invested in to increase their productive capacity. Through such "investments" as education, training, and work experience, it is argued that an individual's knowledge, skills, and abilities expand to generate greater productivity at the workplace.

These investments are hypothesized in the early literature as taking one of two forms– *firm-specific human capital*, or expertise useful to a single employer, and *general human capital*, which is useful to all employers. It was theorized that firms had the economic incentive to fund the former, as workers would be more productive at that specific company and could not parlay this investment to advantage elsewhere in the labor market. Further, it was argued that the onus would be on individual employees to finance general training, as firms would not want to run the risk of losing their investment upon employee turnover.

Regardless of the type of investment made, the augmented productivity wrought through human capital investments is posited to be experienced through increased wages to the individual. This is based on the neoclassical economics approach that suggests that firms will hire workers such that the wage will equal each individual's marginal productivity, with some adjustments made for the cost of training within the firm (Becker 1993, 31-33), among other factors. Strengthening this argument, the human capital model contends that a person's investment choice is based on the predicted long-term earnings stream associated with each available investment option (Becker 1993, 60).[1]

Attempts to econometrically explore the relationship between investments, such as education, and earnings were significantly boosted by the work of Mincer (1974), who operationalized cross-sectional analyses through his advancement of the human capital earnings function. The base of Mincer's model, which has subsequently served as a foundational model in labor economics, is as follows:

$$\ln(\text{wage}_i) = \beta_0 + \beta_1 * \text{education}_i + \beta_2 * \text{experience}_i + \beta_3 * \text{experience}_i^2 + \varepsilon_i.$$

While recognizing the possible need to include marketplace controls, Mincer justified this simple econometric approach on the basis of fundamental hypotheses conveyed in the human capital model:

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[1] A subtle inconsistency in the literature illustrates that when talking about the actions of workers, some theorists suggest that individuals act to maximize earnings (e.g., Shaw, 1984, 322), while others discuss maximizing utility (e.g., Kumar and Coates 1982, 443). While the former is often used to proxy the latter given the near impossibility of quantifying "utility," theoretical completeness requires one to recognize the inherent differences between the two.

> The model of worker self-investment as the basic determinant of earnings might be criticized as giving undue weight to the supply of human capital while ignoring the demand side of the market. Certainly, demand conditions in general, and employer investments in human capital of workers in particular, affect wage rates and time spent in employment, and thereby affect earnings. It should be clear, however, that the earnings function in this study is a "reduced form" equation, in which both demand conditions and supply responses determine the levels of investment in human capital, rates of return, and time worked. The present approach is an initial and simple one, and greater methodological sophistication is clearly desirable. There is a need to relate employers' behavior both as demanders of and direct investors in human capital to the observed distribution of earnings.
>
> The investment-earnings relation in this study is in reduced form also in the sense of describing equilibrium loci in the (human) capital market as well as in the labor market in which human capital is supplied as a factor of production. As Becker describes in his analysis, the cross-sectional earnings function results from two simultaneous structural relations in the (human) capital market. These are demand functions (D_i), which relate individual investments to marginal rates of return, and supply functions (S_i), which relate to the volume of funds that can be obtained for human capital investment to the marginal "interest" costs. Of course, worker demand for self-investment (D_i) is, in part, derived from employer demand for the workers' human capital. (p. 137)

As stated previously, Mincer's "reduced form" approach–the wage equation-is inherently built on the neoclassical economics assumptions required for equilibrium within the human capital and labor markets. It is important to recognize that these assumptions maintain that disequilibria along racial, gender, or occupational lines should not persist, as worker and investment flows should be altered to achieve arbitrage, or the equalization of payments across particular groups. Any such differences in payoffs to occupations are thus attributed to compensating wage differentials (Smith 1976; Kumar and Coates 1982), or non-pecuniary aspects of the job, maintaining a form of "utility arbitrage" across vocations.

While the origins of human capital thought were generally silent on vocational concerns,[2] the model's general stance on occupational choice is best illustrated by an example used by DeBeyer and Knight (1989):

> Once education is determined... workers have a preference-ordering among occupations. There will be one occupation in which a worker with a certain education is more productive, and thus receives a higher wage, than any other. On the one hand, the educated will wish to avoid the unskilled jobs in which their education is less productive and is therefore less highly rewarded. On the other hand, the uneducated will wish to avoid the skill-intensive jobs in which their productivity and pay are lower than in unskilled jobs. (p. 596-97)

While based on economic assumptions, it should be noted that the wage equation and the human capital model's approach to occupational choice–taking the job that maximizes earnings following completion of self-investment–collectively fed into a broader ideology that devalued the role of occupation in terms of explaining wage variation. Duncan (1961) typified this stance by suggesting that occupation was merely an "intervening" variable through which educational differences operated to create earnings differentials. Thus, given the "first education, then occupation" choice mechanism and supposed arbitrage in the labor market, the human capital model advanced a philosophy espousing human capital as the driving force in wage determination given the mechanisms of the market.

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2 As an illustration of the human capital model's "silence" on occupational concerns, the central book on the human capital model–Becker (1993)–fails to include the word "occupation" even once. In Mincer's (1974) fundamental book in deriving the human capital earnings function (i.e., the wage equation), the word "occupation" appears only one time.

Institutional Approach to Occupation

Institutional thinkers resisted the doctrine of human capital given its assumptions that the labor market operated in a fashion similar to capital markets,[3] as well as its "ad hoc" approach to explaining various phenomena (Blaug, 1976). In particular, a specific undercurrent of dissent arose in regard to the theory's silence on occupational issues and the failure of the theory to predict certain vocational outcomes. Ideologically, Mayhew (1971) explicitly rejected Duncan's assertion that occupation serves as an "intervening" variable between education and wages, urging wage analyses to include occupation for "the correct analysis of the economic importance of education" (p. 225). Fogel (1979) took this one step farther, labeling the human capital approach to wage determination "misleading" (p. 26). Fogel thus challenged the notion that wage rates were the result of the interaction of a worker's marginal productivity with the short- and long-run framework of market supply and demand, instead suggesting that one's occupation–not one's personal characteristics–was the key component of the wage-setting process, calling occupational choice "the most fundamental" decision an individual makes in the determination of wages:

> Buyers and sellers of labor services organize their exchange communication around a set of work duties, that is, an occupation (or job, which is simply a specifically defined occupation); thus the forces of wage determination must necessarily be directed to occupations, although wage changes may frequently be applied to entire administrative or bargaining units. Furthermore, as previously stated, individual wage contracting takes place with reference to a specific occupation, and the associated occupation wages–however determined–constrain the contract zone within which agreement is reached. (p. 26).

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3 For discussion of the dissimilarities between the two markets, see Prasch (2004).

Beyond the ideological issues surrounding the true nature of earnings differentials, a number of alternative research streams identified the existence of labor market imperfections that were not easily explained using the human capital framework. Thus, while findings of persistent occupational wage disequilibria (Reder 1955; Eckaus 1973) called into question neoclassical economic assumptions of arbitrage, segmented labor market theorists (Doeringer and Piore 1971) illustrated that different portions of the labor market operated in vastly different manners.[4] In particular, it was noted that the return to education and other forms of human capital was markedly varied across primary and secondary occupational groups (Osterman 1975).[5]

Kerr (1977) justified the presence of these segmentation effects by recognizing that the idea of a "labor market" as examined by the human capital model was a misnomer. Instead, Kerr surmised that the labor market was balkanized along occupational (and geographic) lines due to institutional barriers, such as schooling requirements. This premise gave rise to the notion of a fragmented labor market consisting of an infinite set of non-competing groups, even if those groups are never sharply defined. Arguing that "Painters do not compete with bricklayers, or typists with accountants, or doctors with

4 As summarized by Hagner (2000), primary-sector workers are theorized to enjoy high wages, fringe benefits, satisfactory working conditions, reasonable levels of employment security, possibilities of promotion, and some degree of worker autonomy. Secondary-sector workers, meanwhile, are suggested to experience low wages, minimal or nonexistent benefits, less-than-desirable working conditions, greater probability of layoff and displacement, and harsh work rules or supervisory styles.

5 Cain (1976) and Kruse (1977) criticized Osterman's methodology, suggesting that within-segment regressions suffered from truncation bias of the dependent variable. These criticisms argued that by grouping individuals into "primary" and "secondary" jobs, Osterman was classifying people on the basis of their wage-earning ability. Osterman (1977) responded that this technique was appropriate, for it was the job, and not the individual, that served as the selection variable.

lawyers," (p. 23), Kerr recognized the influence of occupation-specific market forces and wage structures on the determination of wages.

As theorized by Kerr (1977) and Fogel (1979), a consequence of such occupational barriers was that they served to insulate particular labor markets, thereby restricting worker flows and making them noncompetitive. This allows the persistence of nonequilibrium outcomes, which contradicts the arbitrage assumptions of the human capital model. Fogel, in particular, noted that occupational wage disequilibria were able to exist because some workers could not forgo present costs in order to make the necessary investments to enter particular vocations, leading to noncompetitive occupational labor markets. Thus, different occupational environments are able to exist such that returns to human capital vary not only by labor market segment, but also by individual occupation (Rumberger 1987; Freeman and Hirsch 2001; Quinn and Rubb 2005).

Corresponding to this, a primary assertion of the human capital model rationalizes that the positive relationship between education and earnings is attributable to the enhanced productivity gained through schooling. That said, research on sorting models, or the more general name for "signaling" and "screening" effects, has illustrated that educational premiums extend beyond payment for increased productivity (Spence 1973; Layard and Psacharopoulos 1974; Riley 1979; Weiss 1995; Lofstrom 2001; Frazis 2002). This theory suggests that employers, with incomplete information regarding an applicant, will use education as a signal of productivity or other personal attributes in making their hiring decisions. As such, institutional theorists have hypothesized that the positive relationship between schooling and wage is not due to enhanced productivity, but rather to incomplete information in the hiring process.[6]

Review of Occupation-Specific Human Capital

To review, two schools of thought have emerged to explain wage determination in the labor market. Proponents of the human capital model suggest that *education, experience, and training are the primary drivers of earnings,* as individuals select occupations that deliver the greatest payoff to their investments. Human capital theorists cite neoclassical economic assumptions to suggest that augmented productivity wrought through such investment decisions will yield increased wages as established by the supply and demand conditions of the human capital and labor market. Meanwhile, institutionalists contend that *occupation is the primary determinant of wages*, with human capital investments merely representing a means of entry given the presence of vocational barriers, such as schooling requirements. Proponents of this school of thought justify their position by pointing to the shortcomings of the human capital model in explaining such phenomena as occupational wage disequilibria, segmented labor markets, and sorting models.

While forty years of debate between the two schools may have polarized the issues (Leonard 2000), even the most ardent advocate recognizes the validity of each position as

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6 It should be noted here that efforts to obtain an unbiased return on schooling have been relentless, with the primary critique concerning the inability to measure–and thus to include–ability in the wage equation (Griliches 1977). For further discussion, see Card (1998), among others.

it applies to labor market operations (Becker 1993). Thus, it is important to recognize that a simple refinement of the term "human capital" as it applies *to the labor market* may allow the human capital model to incorporate some of the occupation-based considerations brought forth by institutionalist thought. In particular, in reexamining the original composition of "human capital"–both general and firm-specific–as advanced by Becker (1993),[7] a small, but recently revitalized literature has confirmed the presence of a subtle variation therein, *occupation-specific human capital*, that may be the appropriate lens through which the human capital model can consider the occupational phenomena that lie at the heart of the institutional critiques discussed earlier.

While vocational specification of skill has long been established in economics (Smith 1976; Weiss 1971), Shaw (1984) was the first to examine this occupational specificity as it related to the assumed composition of human capital. Defining *occupational investment* as "the accumulation of skills an individual acquires to perform work within an 'occupation'" (p. 320),[8] Shaw presented a nuanced view of human capital, suggesting that general human capital maintained a distinct occupation-specific component that could be carried across employers.[9] However, Shaw noted that, unlike the case of general human capital, individuals would be able to transfer only a certain amount of their

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7 A number of studies have challenged the perfect competition assumptions of the human capital model which suggest that firms will not fund general training, as it is theorized that labor market imperfections allow employers to earn rents on "generally-trained" workers (e.g., Acemoglu and Pischke 1998, 1999).

8 Shaw (1984) defines an "occupation" as "a homogeneous skill classification within which individuals are perfect substitutes in demand and/or have infinite cross elasticities of substitution in supply. Cabinet-makers and engineers, for example, have occupation-specific skills," (pg. 320).

9 Given the portability of occupation-specific human capital as a component of general human capital, the tenets of the model suggests that individuals, and not firms, would bear the brunt of funding occupation-specific human capital. Exceptions do exist, however, as illustrated by construction apprenticeship programs, as firms and unions collectively fund training programs despite worker mobility.

occupation-specific human capital stock in the event of a vocational switch, with the amount inherently depending on the "transferability" between the two respective occupations. In other words, the skills acquired as an art teacher may not be transferable to a career in medicine; in contrast, the training received by an actuary may have considerable transferability to a job as a statistician.[10]

Empirically, Shaw demonstrated the prominent role that occupation-specific human capital played in the determination of wages, as it served as a predictor of wage "far superior" to that of the general experience variable as advanced by Mincer (1974). However, despite this finding, the implications of Shaw's work were largely ignored until very recently, as additional research has confirmed occupation-specific human capital's role as an important predictor of wages. Kambourov and Manovskii (2005), for instance, suggest that an additional five years of occupational tenure is expected to increase wages by 12 to 20 percent. Further, the authors noted that while displaced males between the ages of twenty and sixty suffered, on average, a 15 percent reduction in weekly earnings, those who stayed in the same occupation experienced only a 6 percent drop compared to the 18 percent loss for those who switched vocations.

Additional studies have confirmed the influence of occupation-specific human capital on labor market outcomes. Kambourov and Manovskii (2004a), for instance, suggest that the occupational specificity of human capital, along with increased variability of productivity shocks to those skills in the labor market, explains the increase in wage dispersion and a

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[10] Dolton and Kidd (1998) note that the degree of transferability is inherently an empirical question dependent upon how broadly one treats occupational titles.

decline in wage stability over the last thirty years. Dolton and Kidd (1998) and Gibbs, Ierulli, and Milgrom (2002) illustrate the role occupation-specific human capital has in explaining vocational mobility,[11] while Sullivan (2005b) finds substantial wage influence of occupation-specific human capital through a new approach-a dynamic structural model of career choice that nests job search within a human capital model of occupational and educational choices. Finally, Groen (2006) finds a significant relationship between the size of one's local economic environment and the outcomes associated with occupation-specific human capital.

Therefore, given the growing acceptance of both occupation-specific and industry-specific (Neal 1995; Parent 2000) human capital, it is necessary to revisit the assumed composition of human capital in the basic model. As mentioned earlier, the original formulation of the human capital theory was built upon on the concept of two-dimensional human capital–general and firm-specific-an assumption that has increasingly been called into question (see, among others, Carrington 1993; Thomas and Ong 2002). However a reexamination of productivity in the labor market is suggestive of *five distinct categories* of human capital, segmented on the basis of worker-firm attachment critical to basic human capital theory:

11 Gibbs, Ierulli, and Milgrom (2002) suggest that if a typical worker first gains attachment to an occupation and stays with it while searching across firms, then many of the characteristics of internal labor markets may apply as well to "occupational labor markets (OLMs)." Milgrom (2004) examined internal labor markets and found that, especially at higher ranks, there exists more evidence of occupation-based ports of entry than firm-based ports of entry. In other words, a firm is more likely to hire someone in the same occupation from a different firm than promote from within.

MARKET-WIDE	EMPLOYER-SPECIFIC
(1) General	(4) Firm-Specific
(2) Occupation-Specific	(5) Job-Specific
(3) Industry-Specific	

The "market-wide" category contains the components of human capital that are portable across employers, thereby putting the theoretical burden on employees to acquire these skills on their own. Meanwhile, the "employer-specific" classification includes the two components that are unique to the worker-firm relationship and would be lost upon its termination. While the research has yet to identify "job-specific" components, this inherently allows for the inclusion of the productivity increases attributable to knowing the best methods, or "shortcuts," available at specific tasks in one's job that would be lost if the individual was reassigned elsewhere in the firm but with a similar role. For example, an insurance claims agent responsible for Michigan may have significant familiarity with all of the necessary forms and procedures after working in that role for five years. However, if that person were moved across the hall and put in charge of Georgia claims, there would be a loss of job-specific capital that affects that person's productivity given his or her initial unfamiliarity with the corresponding procedures for the new state. Therefore, failure to identify job-specific components excludes an important dimension of one's productivity on the job and the corresponding utility inherent in the position.

Drawing clear distinctions between the five classifications of human capital represents a subtle theoretical variation from Shaw (1984) and Thomas and Ong (2002), among others, who inherently advance an intertwined notion of occupation-specific and purely general human capital.[12] In contrast, this clear partitioning allows for greater theoretical ease in explaining certain labor market phenomena using human capital principles (see following section), and distinctions between each type are made in light of well-defined occupational and industrial barriers to entry that are responsible for the balkanization of the labor market (Kerr 1977).[13] In other words, there are clear occupational effects at work in the labor market operating through these barriers to entry, such as requirements for a master's in *business administration* or a Ph.D. in *economics*. In addition, Becker's (1962) original definition of "general" human capital suggests that it can be transferred across all employers; in contrast, occupation-specific (and industry-specific) human capital is not applicable to all employers, leaving notions of the intertwined nature of occupation-specificity contradictory to the basic theory. Further, research has illustrated markedly contrasting effects of each of the forms of human capital on wage estimates, with occupation-specific human capital generally outpacing other forms, including general, in terms of importance to establishing wages (Shaw 1984; Milgrom 2004; Kambourov and Manovskii 2005; Sullivan 2005a, 2005b).[14]

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12 Speaking on the application of occupational investment across vocations, Shaw (1984) suggested that, "Transferability is always greater than zero because a portion of postschool investment is completely general (for example, learning to communicate with others)" (p. 321).

13 A controversial theoretical alternative would be to suggest that, in light of occupation-specific and industry-specific human capital, the idea of "general" human capital contains an empty set. This is because even commonly referenced examples of "general" human capital, such as general literacy or the ability to interact with people, inherently are applied only within the context of a given job. Literacy may not be required for agricultural workers. Being able to interact with people may not affect the productivity of computer programmers. While this point is not made in this paper, it could be alternatively argued that "human capital" is defined only by how it is applied to the characteristics and duties of a particular job.

14 Shaw's (1984) illustration of occupation-specific human capital's dominance over a measure of general human capital has been found to be consistent with later studies demonstrating the prominent role that occupation-specific human capital plays in the determination of wages. However, the impact of other forms of human capital has been a source of debate. In particular, while Kambourov and Manovskii (2004a, 2005) suggest industry-specific human capital had little effect, Sullivan (2005a) found the opposite, indicating that the former's failure to predict significant industry-specific effects was due to the failure to include

An important extension of the reclassification of human capital recognizes that all human capital investments–and thus, an individual's human capital stock-can be partitioned into each of the five categories above. While vague boundaries between classifications and the impossibility of quantifying human capital investments makes this a theoretical exercise,[15] it serves as a means of understanding the impact of various investments on labor market outcomes such as wage and mobility. For instance, consider the following hypothetical comparison between a bachelor's degree in engineering and a bachelor's degree in liberal arts:

Figure 1 illustrates that each investment–in this case, a bachelor's degree–can be examined as to the amount of human capital imparted to each occupation, industry, firm, and general category. While Figure 1 provides only a partial list of human capital dimensions, it illustrates that an engineering degree may instill an extraordinary amount of knowledge and skills within engineering occupations, as well as some exposure to specific firms and industries. However, an engineering curriculum may be of much less use in introducing the necessary expertise to teach a high school class or work as a newspaper reporter. Meanwhile, a broader liberal arts degree may provide more pure general training, as well as equip one with some proficiency across a wide range of

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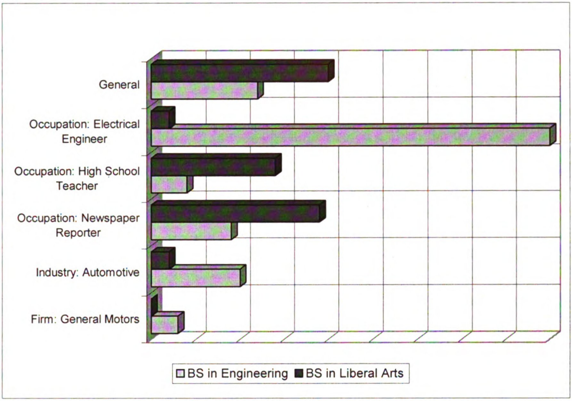
within-firm occupational switches. While the effect of industry-specific human capital is an issue of debate, the role of firm-specific expertise in wage determination has increasingly been seen as marginal (Lazear 2003; Kambourov and Manovskii 2004a, 2005; Milgrom 2004; Poletaev and Robinson 2004).

15 As noted in Kambourov and Manovskii (2005), the definition of "occupation" plays a significant role in determining the accumulation–and applicability-of human capital in that vocation. For instance, if the occupational spectrum were divided to include a category for "professors," this would inherently suggest that physics and economics professors are perfect substitutes. Thus, greater refinement would be needed to accurately model labor market phenomena.

FIGURE 1. Partial Dimensions of Human Capital in Bachelor's Degrees in Engineering and Liberal Arts



occupations and industries, but might not provide as great a depth of training in any one field.

The recognition of the multidimensional nature of human capital within this five-category system represents a simple elaboration on the transferability of occupation-specific human capital as denoted by Shaw (1984). She contended that time spent within an occupation, *i*, could be applied to a separate occupation, *j*, by the degree of transferability between the two occupations, or γ_{ij} (p. 321).[16] This suggests, for example, that a year

16 In an effort to establish a matrix of transferability between occupations, Shaw (1984) examined occupational mobility-movement across occupations-using the Current Population Survey. However, this

spent as an accountant not only expands one's occupation-specific human capital stock as an accountant, but also expands one's specific stock as an actuary, engineer, and physicist by the degree of transferability between the respective occupations given a nonzero γ_{ij}.

In light of the five partitions of human capital advanced earlier, the implications of the multidimensionality of investments suggest that each person inherently maintains a stock in each of V vocations, I industries, F firms, and J jobs, as well as a general category–or a Φ= VxIxFxJx1 human capital matrix. Each component of that matrix, ϕ_{vifj1}, is determined by the sum of education, experience, training, and other forms of learning applicable to that cell of the matrix, depreciated by some measure of obsolescence.[17] Thus, while this may be quantitatively intractable, it is important to note that individuals use only a single component of that matrix, ϕ_{vifj1}, in any one job.[18]

It is important to note a couple of intricacies in constructing measures of the components of the human capital matrix, ϕ_{vifj1}. First, while researchers will typically be limited to duration of schooling or within a particular occupation as a means of estimating specific

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approach introduces a significant amount of noise given the occupational coding errors of the CPS that bias vocational switching studies (Kambourov and Manovskii, 2004b).

17 The rate of obsolescence as applied to this theoretical matrix would allow for heterogeneity given varying degrees of technological change, among other factors, across occupations, industries, firms, and jobs. For instance, the rate of obsolescence of one's skill in the occupation of "high school algebra teacher" may be quite different than the rate of obsolescence of one's expertise as a "computer programmer" (Bishop, 1998).

18 As a matter of precision, it is therefore important to recognize that other ϕ_{vifj1} in the matrix are not lost or "destroyed" (Kambourov and Manovskii 2005) if unapplied. They remain inherent to the person, just not used.

human capital, one must recognize the inherent differences in intensity that may exist across investment options (Shaw 1984; Sullivan 2005a). In other words, one might expect a higher intensity level of investment for one's freshman year at an Ivy League school compared to a local community college. Second, this intensity will not be linear over time, as there may be diminishing marginal returns to additional years spent in a particular position. In other words, once someone has mastered the tasks specific to a particular job, there may not anything left to learn, making additional time spent in that role insignificant to the accumulation of additional human capital.

Applications of Occupation-Specific Human Capital

While the full labor market implications of the redefinition of human capital extend beyond the bounds of this paper, the introduction of *occupational* specificity into the human capital model represents a subtle refinement of the theory capable of explaining certain occupational phenomena noted by institutionalist critiques. Of most importance has to do with the underlying source of discord between institutionalists and human capital theorists regarding wage determination in the labor market. As discussed earlier, human capital theorists contend that self-investment is the primary determinant of earnings while institutionalists argue that occupation in the principal factor. On the surface, these stances seem to conflict; however, they have been merely addressing opposite sides of the same coin. In other words, when viewed together through the lens of occupation-specific human capital, the two positions can be unified to provide a simple, eloquent framework within which to understand the relationship between self-investment, occupation, and earnings.

The capacity to fuse these seemingly conflicting theories rests upon the recognition of the five different dimensions inherent in each human capital investment, as previously described. What this suggests is that when individuals make investment decisions, they are inherently choosing to augment each respective cell of their human capital matrix, ϕ_{vifjl}. However, different investment options alter each ϕ_{vifjl} in dissimilar ways, as individuals make choices to acquire human capital along specific dimensions (for example, work experience in the automotive industry, schoolwork in psychology, etc.). Upon this conscious or unconscious accumulation of human capital along occupational, industrial, firm, job, and general dimensions, individuals will then seek out employment that provides the best utilitarian returns on their investment.

Generalizing this discussion to a specific investment (education) and dimension of human capital (occupation), the reconciliation of the two schools of thought relies on the recognition of the occupational components of schooling options, as acknowledged by Fogel (1979) and Orazem and Mattila (1991). As such, when individuals make schooling choices, they are, consciously or not, altering their human capital stocks along specific occupational dimensions. For instance, extensive coursework in statistics builds substantial occupation-specific human capital for particular vocations, such as actuaries, statisticians, economists, and computer programmers, among others. Therefore, upon completion of schooling, an individual will seek employment in professions that will inherently yield the largest payoff to the human capital stock, which, after the person's education, is largest within certain occupational dimensions.

This advancement suggests that establishing the primary determinant of wages between education and occupation is inherently a chicken-or-egg proposition. This perspective is consistent with the importance the human capital approach places on education, as it corroborates the notion that individuals will select the occupation that offers the maximum return on their investment. At the same time, this hypothesis confirms the institutional emphasis on occupation in wage determination, as the occupational components of the respective schooling options play a prominent role in occupational selection decisions given the inherent wage implications of occupation-specific human capital across the vocational spectrum (Kambourov and Manovskii 2005; Sullivan 2005a).[19]

While different educational options will instill varying levels of occupation-specific human capital, it is important at this point to denote the presence of vocational schooling requirements that have moved some to suggest that education merely serves as a means of entry to occupations (Fogel 1979). These formal and informal schooling barriers undoubtedly play a role in the labor market (Taubman and Wales 1973), and individuals often make occupational decisions *before* educational decisions, contrary to the "first education, then schooling" example cited by DeBeyer and Knight (1989). For instance,

19 This suggestion not only is confirmed by findings of the dominant role played by occupation-specific human capital in the determination of wages, but also allows for variability in the payoff to vocations and their respective skills, or the "productivity shocks to occupations" noted by Kambourov and Manovskii (2004a).

medical students do not push through four years of medical school and three years of residency and only *then* decide to become physicians–the occupational selection was what drove educational choice, making it, in some cases, a simultaneous outcome.

The refined theory of human capital composition expressed here can account for the earnings impact of vocational schooling requirements on educational and occupational decisions.[20] In particular, the presence of schooling requirements recognizes that individuals must necessarily acquire a certain level of occupation-specific human capital before they are able to reap a substantial payoff. In other words, the return to each ϕ_V may not be linear; instead, in the presence of educational barriers, the return to schooling within a given occupation may resemble a stepwise function. Not only does this explain the educational premiums attached to degrees (Belman and Heywood 1991; Belzil and Hansen 2002), but it also explains the common sense recognition that taking an introductory class in physiology as a college freshman would have zero return as occupation-specific human capital in the vocation of "physician" absent further pursuit of a medical degree.[21] Thus, individuals may pursue educational choices based on the acknowledgment of significant payoff only to specific levels of occupation-specific human capital.[22]

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20 Rumberger (1987), for instance, demonstrates diminished return to education beyond the schooling requirements of the particular job.

21 Students may maintain a level of uncertainty regarding the schooling requirements of occupations (Robst and Cuson-Graham 1999).

22 The introduction of potential step-wise returns to self-investment inherently contradicts the productivity-wage relationship assumed within the human capital model. This assumption, based on neoclassical economic assertions, suggests that increases in applicable productivity (such as that wrought through a introductory physiology class) would be met with an increase in wages in the labor market.

From the labor demand perspective, the very existence of these schooling requirements has been a source of contention in the debate between these two schools, as their presence has typically been explained by the incomplete information held by firms in the hiring process. While this represents the basic modus operandi of sorting models, the recognition of occupation-specific human capital requires a subtle reformulation of this approach.[23] In their quest to select the most productive employee in light of incomplete information, firms base their decisions on a variety of signals, including an applicants' completion of specific educational tracks. Employers then utilize these signals to estimate the occupation-specific human capital stock imparted to the applicant given the firms' knowledge about the curriculum and intensity of the school.

Such an explanation also lies at the heart of occupational licensing issues in vocations requiring individuals to obtain specific educational degrees in order to become certified in a specific profession, such as physicians and teachers. These educational mandates for vocational entry, such as a bachelor's degree in education, are based on the belief that the required schooling curriculum imparts, at a minimum, a specific, *known* amount of occupation-specific human capital that would allow one to adequately perform in a given

While this may be true in general, this obviously does not hold within occupational markets given the presence of vocational requirements (such as schooling barriers). Such a finding was stressed in Gottschalk (1978); however other efforts (e.g., Hellerstein, Neumark, and Troske 1999) have maintained the applicability of the productivity-wage correspondence.

23 As noted in Weiss (1995), it is important to recognize that sorting models inherently do not contradict human capital principles, as they are built upon the same basic principles–profit-maximizing firms and utility-maximizing workers. Sorting models inherently are the ripple in the equation proposed by the human capital model created by incomplete information in the labor market between firms and workers.

profession. Regardless of the motivation,[24] the formal and informal requirements of known levels of occupation-specific human capital (education, work experience) represent the inherent barriers denoted by Kerr (1977) that balkanize the labor market, thereby producing noncompeting groups that restrict worker flow and allow for the persistence of nonequilibrium outcomes, including the failure of labor market arbitrage.

While never referenced using these terms, occupation-specific human capital has inherently been presented as an explanation for one of these contested outcomes, namely segmented labor markets. Picard (1993), in particular, suggests that segmentation is a by-product of differences in the type of labor required in various employment situations; in particular, jobs in the secondary market involve only a few skills, thus denying workers the ability to accumulate a repertoire of transferable skills necessary to gain entrance into a primary-sector job. While others have referenced secondary work as "mini-skilled" (Reiter 1991) and "deskilled" (MacDonald and Sirianni 1996), this argument has suggested that workers are stuck in the secondary labor market because their work experience fails to render them more marketable over time.

While a full explanation of segmented labor markets may involve a complex interaction of supply- and demand-side factors (Bailey and Waldinger 1991), Picard's explanation corroborates the expected outcome associated with occupation-specific human capital in a labor market rife with vocational barriers and incomplete information. Essentially,

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24 While some occupations, such as teachers and physicians, may use educational requirements as a means of ensuring public health and safety, other groups may insist on such mandates as a means of restricting competition in order to increase market power.

Picard's description suggests that workers in the secondary labor market have limited ability to move into the primary labor market given their inability to develop occupation-specific human capital due to the restricted set of skills necessary for secondary work and the correspondingly low degree of transferability of those minimal skills into primary occupations. Thus, considering that firms will hire the applicant with the presumed maximum value of the appropriate ϕ_{vifjl} for a given job, the lack of any known investment that yields significant transferability in an environment of incomplete information will lead such applicants to be continually passed over for work in the primary sector regardless of their intrinsic capacities.

Given this explanation, the known accumulation of occupation-specific human capital represents the balkanizing "barrier" not only between individual occupations, but also between the primary and secondary sectors of the labor market. Not only would the skills of primary-sector jobs maintain a higher degree of transferability that allows for greater movement of workers across vocations *within* the sector (e.g., from accountant to teacher), but the accrual of occupation-specific human capital would also intrinsically serve as a signal of unobservable factors regarding given applicants. Either way, the accumulation of occupation-specific human capital serves as the foundation upon which vocational and earnings outcomes are determined. As such, given the occupational implications of educational investments, the underlying question regarding the primary determinant of earnings–whether education or occupation–inherently fails to see the forest for the trees; the correct answer is "both."

Applications to the Wage Equation

A phenomenon commonly referenced in the segmented labor market theory literature recognizes the stark contrasts in the return to education between the primary and secondary sectors (Osterman 1975; Dickens and Lang 1985; Sakamoto and Chen 1991). However, such a determination is only a part of the story. Thus, while it has become increasingly apparent that the return to education is minimal among a certain cluster of jobs in the secondary market, the return to education actually varies greatly *within* the primary market, as illustrated by the varying returns to schooling across the entire occupational spectrum (Eckaus 1973; Quinn and Rubb 2005; Sullivan 2005a).

While dissimilar educational returns by occupation may have represented a source of institutional critique, such results fall directly out of a human capital model incorporating the occupational specificity of education, or, more broadly, the five dimensions inherent in each investment choice. Too often, data restrictions lead researchers to view education as a homogeneous duration variable while ignoring other vital aspects–including the occupational components of the schooling choice (Orazem and Mattila, 1991)–that are inherently responsible for generating certain labor market outcomes. However, education is far from homogeneous, engendering markedly different responses within an individual's human capital matrix depending on the curriculum, intensity, and other factors associated with the schooling choice. Correspondingly, one would expect a degree rich in occupation-specific human capital (e.g., engineering) to produce large wage returns when applied within the respective vocation, as compared to a broad-based degree (e.g., liberal arts). Further, the theory of occupation-specific human capital would expect that any vocational switch would generate a significant loss of rents, a finding confirmed by Kambourov and Manovskii (2005).

Given the influence of occupation-specific human capital on schooling outcomes in the labor market, it is imperative to recognize how the characteristics of occupations and schooling options interact to affect the potential level of human capital accumulation, or the increase in ϕ_{vifj1}, across investments. Thus, beyond duration effects of schooling, the ability of education to impart specific knowledge along an occupational dimension of the theorized human capital matrix depends heavily on the duties and tasks required by the position. For instance, some jobs, such as those of economists or physicists, rely heavily on educational investments to impart the expertise necessary to succeed in the position; in other words, the accumulation potential through schooling along these occupational dimensions of the matrix is quite significant. However, for other vocations, such as electricians or bricklayers, traditional educational programs may have scant applicability in increasing productivity given that the duties of the position are difficult, if not impossible, to teach through classroom learning; instead, human capital accumulation within those cells of the matrix relies heavily on work experience and on-the-job training.

While it is important to recognize that the characteristics of an occupation may dictate the varying success of specific investments (e.g., education vs. experience), it is also imperative to note that marginal productivity of any investment is not necessarily linear; rather, the capacity of such investments to inspire growth in one's expertise is, once again, based on the characteristics of the job. For example, while basic math skills learned in high school may be suitable for one to run a cash register, additional mathematics training may yield little, if any, gains in productivity. Also, occupational barriers may restrict marginal productivity, as demonstrated by truck drivers: after learning the "tricks of the trade" in their first year, movement from one's sixteenth to seventeenth year on the job may yield little, if any, additional productivity gains given the presence of speed limits and hours-of-service regulations. Taken together, this suggests that additional years of schooling may not yield significant productivity gains within the applicable ϕ_{vifj1} value within one's human capital matrix. Rumberger (1987) confirms these findings, illustrating declining marginal returns to education beyond the schooling requirements of one's respective job.

Given these outcomes of the model using occupation-specific human capital, the failure to find a sizeable education premium in the secondary market relies on the fact that secondary jobs, by definition, do not require a significant amount of occupation-specific human capital to adequately perform the required tasks of the position. As such, the applicability of additional schooling beyond a necessary level would yield diminishing marginal returns given the productivity restrictions of a particular occupation that fails to provide firm incentives to hire educated workers at a premium rate. Further, worker investment in work experience in these secondary-sector jobs only perpetuates the cycle, as the failure of these jobs to provide an accumulation of occupation-specific human capital leaves such workers "stuck" in these roles given primary-sector skill requirements. On the contrary, it should be noted that education and experience produce comparatively greater marginal earnings gains given occupational characteristics that allow for larger productivity ranges in the primary sector.

Summarizing to this point, it is apparent that the five-dimensional composition of investment options and the characteristics and productivity restrictions of occupations justify occupation-specific returns to such investments. However, the standard application of the human capital model–the wage equation–fails to allow for this vocational specificity, as typical wage regressions implicitly assume equality of investment return across the vocational spectrum (Freeman and Hirsch, 2001). Therefore, given the implications of this paper, it is imperative to test the specification of the standard wage equation and its common exclusion of education-occupation interactions.

Beyond the use of interactions, the specification of occupation itself in wage equations represents an unexplored, yet subtly disruptive influence on research findings scattered throughout labor economics research. Given the pervasiveness of the wage equation in the field, the failure to examine how occupational specification affects other coefficients in the model is surprising. In particular, efforts to "include occupation" in the standard wage model are extremely inconsistent, as the attempts in the literature range from minimal (Arai 2003; Wheeler 2001) to sophisticated (Hirsch and Macpherson 2004). However, how one specifies occupation can produce unintended biases on other coefficients.

As an example, consider a standard wage equation that includes an occupational control for "legal occupations," which would include such things as lawyers, judges, and paralegals. However, upon estimation, the model will attribute the earnings differentials between individual occupations within the category–such as lawyers and paralegals–to any systematic difference between individuals within the two specific professions. In the example of lawyers and paralegals, for instance, a regression model will attribute the earnings differential between the two professions to the effect of education considering the former will have substantially more. While this begs the chicken-or-egg question regarding the source of the payoff–the occupation or the education–the example illustrates, more broadly, that systematic differences across vocations *within* a category may be misattributed, whether it be to education, race, citizenship status, or other potential variables. In other words, simplistic efforts to "control for occupation" may produce biased coefficients given concealed relationships between vocation and other control variables. Given this potentiality for bias, this study will not only examine education-occupation interactions, but also address how occupational specification affects other coefficients in the model.

DATA AND MODEL

To examine occupational specification and the use of vocation-education interactions in the wage equation, this paper will utilize data extracted from the 2000 United States Census One-Percent Public Use Micro Sample (PUMS) Files. As its title indicates, the sample is drawn from the decennial census, with a standard battery of questions aimed at demographics, income, occupation, and work habits for the year 1999. This cross-sectional data set, while failing to contain a union variable, is otherwise ideal due to its enormous sample size and its expansive occupational classification system, allowing for a very detailed exploration of particular labor market questions.

Since hourly wage is not an item in the PUMS file, it is calculated by dividing one's annual income by the total number of hours worked in the previous year. Considering that the goal of this paper is to examine basic features of occupation in the wage equation, and not to isolate *precise* coefficients, the fact that this calculation of wage contains a number of statistical caveats (Borjas 1980) is not particularly worrisome. Also, the derivation of hourly wage is limited only to work performed outside of self-employment given the different environments faced by employees and the self-employed (Fuchs, 1982; Gill, 1988; Carrington, McCue, and Pierce 1996). Those with wages of less than $3 per hour were discarded.

Given the importance of the occupation and education variables in this study, it was imperative to eliminate all potential bias generated through allocated, or "hot-carded", entries for these observations (Hirsch and Schumacher, 2004). Thus, for inclusion in this analysis, individuals within the PUMS file must have reported their own occupation and education. In addition, the sample was pared down to include only those who worked full time (35+ hours per week, 48+ weeks per year) and were between twenty-five and sixty-four years old. Finally, the analysis was limited to men in order to remove any potential gender effects (Oaxaca 1973; Macpherson and Hirsch 1995). The resulting sample included 395,244 males who met the eligibility criteria. The data is described in detail in Table 1.

The baseline wage model applied in this study utilizes common human capital variables included in standard wage equations, as shown below. It should be noted that industry and occupation, as well as the occupation-education interactions, will be excluded from initial models to establish a baseline comparison:

$$\log(wage) = \beta_0 + \beta_1 education + \beta_2 race + \beta_3 marital\_status + \beta_4 citizenship\_status + \beta_5 disability\_status + \beta_6 state + \beta_7 age + \beta_8 age^2 + \beta_9 industry + \beta_{10} occupation + \beta_{11} occupation*education + \varepsilon$$

In regard to the education variable, there has been a stream of research debating the applicability of the linear schooling variable, which was the original suggestion of Mincer (1974). While the linear variable continues to be employed by a number of studies (e.g., Anderson and Shapiro 1996), one of the limitations of the linear specification is that it assumes an equal effect of schooling across all education intervals.

TABLE 1. Sample Means

Human Capital Variables	*Mean*	*Human Capital Variables*	*Mean*
Education		*Industry*	
Less than 9 years	0.032	Agriculture	0.016
High school, no diploma	0.066	Mining	0.009
High school diploma	0.276	Utilities	0.019
College: Less than 1 year	0.073	Construction	0.101
College: One or more years	0.156	Manufacturing	0.227
Associate's Degree	0.075	Wholesale Trade	0.053
Bachelor's Degree	0.196	Retail Trade	0.093
Master's Degree	0.070	Transportation	0.065
Professional Degree	0.026	Information	0.032
Doctorate Degree	0.015	Finance, Insurance, Real Estate	0.054
Race		Professional, Management	0.059
White	0.842	Administrative Support	0.027
Black	0.074	Education	0.044
Native American	0.012	Health Care	0.044
Asian	0.038	Recreation, Entertainment	0.013
Pacific Islander – Hawaiian	0.002	Food Service	0.029
Other	0.050	Service - Other	0.040
Marital Status		Public Administration	0.065
Married	0.729		
Divorced or Separated	0.116		
Widowed	0.005		
Never Married	0.149		
Age	41.810		
Non-Citizen	0.064		
Disability Status	0.140		
Wage	$21.24		

This presupposition, however, has been rejected in favor of using a series of dummy variables to signify different educational attainment (Belzil and Hansen 2002). This allows for the possibility of "diploma effects" that are generally supported in the signaling literature (Hungerford and Solon 1987; Belman and Heywood 1991). The rejection of the linear schooling specification also allows this study the flexibility to explore how occupation interacts with education at different levels of schooling. The ten mutually exclusive educational categories used in this study, and their respective means, are also listed in Table 1.

TABLE 2. Occupational Specifications

22 Major Occupations (SOC ##)	*Count*	*Education/Training Categories*	*Count*
Management (11)	51,311	Professional Degree	10,326
Business and Financial Ops. (13)	16,111	Doctor's Degree	3,595
Computer and Math. Science (15)	14,536	Master's Degree	3,057
Architecture and Engineering (17)	16,685	Degree Plus Experience	33,183
Life, Physical, Social Sciences (19)	4,764	Bachelor's Degree	58,951
Community and Social Services (21)	5,039	Associate's Degree	8,192
Legal (23)	4,011	Vocational Award	17,522
Education, Training, and Library (25)	8,681	Work Experience	65,021
Arts, Design, Entertain., Media (27)	5,906	Long-Term On-the-Job Training	47,330
Healthcare Practitioner and Tech. (29)	9,594	Moderate-Term On-the-Job Training	85,907
Healthcare Support (31)	1,418	Short-Term On-the-Job Training	62,160
Protective Service (33)	14,022		
Food Preparation and Serving (35)	6,994		
Building and Grounds Cleaning, (37)	11,412		
Personal Care and Service (39)	2,600		
Sales (41)	38,960		
Office and Admin. Support (43)	26,025		
Farming, Fishing, and Forestry (45)	3,514		
Construction and Extraction (47)	35,157		
Installation, Repair, and Mainten. (49)	32,169		
Production (51)	49,598		
Transportation and Material Mov. (53)	36,737		

Since the inclusion and specification of vocational controls in the wage model lies at the heart of this discussion, some mention of the occupational coding structure is required. The PUMS data categorizes workers according to a three-digit, Census 2000 occupational coding system. From there, the PUMS file converts these classifications into their respective six-digit occupational codes within the 2000 Standard Occupational Classification (SOC) system. Originally introduced in 1977, the SOC system covers all vocations in which work is performed for pay or profit, and is based on the work performed within the job in addition to the similarity of skills, education, training, or credentials required for the profession.[25] The resulting structure allows for twenty-three major occupational categories (including one military grouping), each of which is

25 Bureau of Labor Statistics. *Revising the Standard Occupational Classification System.* June 1999. http://www.bls.gov/soc/socrpt929.pdf.

denoted by a distinct first-two-digit code. For example, "11-XXXX" denotes all management occupations, while "13-XXXX" signifies all business and financial professions. These classifications become narrower as one moves to the third, fourth, fifth, and sixth digits of the coding structure, producing a classification hierarchy that can be applied to group occupations together on a number of different levels. As a result of the SOC classification, the PUMS data utilized here includes the 22 two-digit groupings (excluding military) that contain each of the distinct 92 three-digit and 505 six-digit classifications explored in this study. A listing of each of the 22 major categories, along with their respective observation tallies, is provided in Table 2.[26]

RESULTS

Occupational Specification

The initial examination of the wage equation explores occupational specification without addressing the inclusion of occupation-education interactions. These results, presented in Table 3, provide six models that analyze varying specifications of vocation in the wage equation. Model 1 presents the base wage equation minus industry and occupation, with Model 2 incorporating industry (but not occupation) to provide an intermediate step in

26 Because of minor incongruences between the occupational structures of the 2000 Census and the SOC, 31 low-population occupations were aggregated into 13 aggregated categories.

TABLE 3. Wage Determination, Males, Full Sample, Series of Education Dummies

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*
Education						
Less than 9 years	-0.244 (45.99)	-0.215 (41.45)	-0.194 (37.89)	-0.183 (36.12)	-0.172 (34.19)	-0.164 (32.79)
High school, no diploma	-0.110 (30.07)	-0.101 (28.30)	-0.094 (26.77)	-0.088 (25.25)	-0.083 (24.20)	-0.079 (23.15)
High school diploma (No college)	Base	Base	Base	Base	Base	Base
College: Less than 1 year	0.101 (28.99)	0.094 (27.37)	0.079 (23.44)	0.065 (19.54)	0.059 (17.91)	0.054 (16.34)
College: One or more years	0.150 (56.55)	0.142 (54.28)	0.118 (45.41)	0.096 (36.96)	0.086 (33.43)	0.076 (29.91)
Associate's Degree	0.184 (52.99)	0.171 (50.22)	0.146 (43.32)	0.107 (31.51)	0.095 (28.36)	0.086 (25.84)
Bachelor's Degree	0.435 (173.55)	0.409 (160.54)	0.349 (134.39)	0.306 (111.78)	0.275 (99.36)	0.251 (90.14)
Master's Degree	0.541 (149.76)	0.540 (146.57)	0.461 (124.09)	0.430 (111.06)	0.400 (102.85)	0.362 (92.02)
Professional Degree	0.805 (147.13)	0.775 (136.61)	0.752 (133.94)	0.653 (94.66)	0.548 (73.90)	0.410 (49.52)
Doctorate Degree	0.622 (88.57)	0.681 (95.81)	0.627 (89.18)	0.598 (81.97)	0.537 (69.76)	0.482 (61.28)
Race						
White	Base	Base	Base	Base	Base	Base
Black	-0.127 (38.16)	-0.117 (35.94)	-0.099 (30.70)	-0.082 (25.72)	-0.073 (23.14)	-0.064 (20.61)
Native American	-0.114 (14.88)	-0.106 (14.15)	-0.100 (13.52)	-0.094 (12.84)	-0.090 (12.46)	-0.086 (12.10)
Asian	-0.061 (12.86)	-0.064 (13.93)	-0.047 (10.31)	-0.071 (15.77)	-0.067 (14.94)	-0.069 (15.57)
Pacific Islander	-0.037 (2.06)	-0.035 (1.99)	-0.033 (1.90)	-0.024 (1.42)	-0.022 (1.28)	-0.017 (1.01)
Other Race	-0.131 (30.46)	-0.115 (27.31)	-0.101 (24.33)	-0.091 (22.29)	-0.086 (21.27)	-0.079 (19.62)
Marital Status						
Single, Never Married	Base	Base	Base	Base	Base	Base
Married	0.190 (74.27)	0.175 (70.09)	0.159 (64.36)	0.155 (63.72)	0.148 (61.13)	0.142 (59.11)
Separated, Divorced, Widowed	0.061 (17.63)	0.050 (14.91)	0.043 (12.93)	0.042 (12.96)	0.039 (12.12)	0.038 (11.74)
Age	0.052 (70.63)	0.050 (69.65)	0.048 (68.12)	0.048 (68.78)	0.047 (68.25)	0.046 (68.01)
Age^2	-0.0005 (58.90)	-0.0005 (57.45)	-0.0005 (56.40)	-0.0005 (56.58)	-0.0004 (55.96)	-0.0004 (55.75)
Non-Citizen	-0.161 (40.85)	-0.145 (37.64)	-0.135 (35.46)	-0.136 (36.35)	-0.129 (34.65)	-0.120 (32.39)
Disabled	-0.079 (31.96)	-0.073 (30.38)	-0.066 (27.81)	-0.062 (26.43)	-0.058 (24.84)	-0.054 (23.38)

TABLE 3. Wage Determination, Males, Full Sample, Series of Education Dummies (cont.)

State	X	X	X	X	X	X
Industry		X	X	X	X	X
Occupation (7 controls)			X			
Occupation (22, two-digit SOC)				X		
Occupation (92, three-digit SOC)					X	
Occupation (505, six-digit SOC)						X
R-squared	0.2733	0.3089	0.3282	0.3450	0.3584	0.3755
Adjusted R-squared	0.2732	0.3087	0.3281	0.3448	0.3581	0.3746
Observations	395,244	395,244	395,244	395,244	395,244	395,244
F-Test Against Model 1	X	1197.01		1137.48	489.39	*
F-Test Against Model 2	X	X		1035.99	338.35	*

Note: Absolute value of t-statistic in parentheses.

the analysis.[27] Model 3 takes a first attempt at including occupation, as it envelops seven vocational controls in an effort to simulate crude occupational categorizations that arE often applied in the literature. Model 4 expands this vocational specification to twenty-two classifications based on commonality of the first two digits of each occupation's respective SOC code. Model 5 magnifies this effect even further, including ninety-two

27 Wage equations that exclude job characteristics, such as occupation and industry, typically encompass attempts to isolate the return to education. The method of estimating the return to schooling through the wage equation has run into a number of issues, however its failure to include occupation has yet to be addressed head-on. In particular, the simultaneous relationship between education, occupation, and wages produces biased schooling coefficients in light of the above conversation of occupation-specific human capital and the concurrent decision-making between schooling and career decisions. As such, even a rudimentary examination of the issue at least calls into question the practice of trying to isolate educational returns absent occupational controls: using the principles of Baron and Kenny (1986), it can be illustrated that occupation serves as a mediator between education and wages, an effect that is statistically significant. While it is undeniable that education plays a key role in occupational attainment, the disentanglement of occupation from the return-to-schooling has yet to be fully examined. For a full discussion of mediation results, see Appendix A.

occupational controls based on SOC three-digit commonality. Finally, Model 6 presents the maximum specificity–including controls for each unique six-digit SOC code.

While the results of individual models provide some insight, the more important results stem from an examination of the trends across models. An initial analysis recognizes the influence of occupational concerns in explaining wage variation in the model; not only does the inclusion of job characteristics (industry and occupation) boost the adjusted r-squared from 0.2732 (Model 1) to 0.3746 (Model 6), but the mere elaboration of vocational specification from crude (Model 3) to refined (Model 6) was able to explain an additional 5 percent of the variation in wages. The inclusion of occupational controls is undoubtedly significant.

In turning to individual variable trends, it is important to note that Table 3 presents the coefficient on the variable in the log(wage) equation followed by the absolute value of the t-statistic below it in parentheses. Given the earlier discussion regarding the inherent relationship between education and occupation, it should be rather unsurprising that the refinement of vocational controls in the wage equation considerably influences schooling returns. For example, turning to the effect of a bachelor's degree against a high school diploma, Model 1 suggests that someone with a four-year degree is expected to earn 54.5 percent more than a high school graduate without any college experience.[28] However, upon adding simple controls (Model 3), that effect falls to 41.8 percent; elaborate controls (Model 6) deflate the effect of a bachelor's degree to 28.5 percent. Similarly, all

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28 Note that percentages drawn from the wage equation are determined by $e^{\beta}-1$.

education effects dampen in light of additional vocational controls, systematically moving toward zero as occupational categorization expands.

While the effect of occupational refinement on schooling returns may be expected, its influence on other parts of the wage equation represents the subtle means through which specification acts to shape research findings. In particular, given the wage equation's utilization as a means to explore racial discrimination, it is more than a little eye-opening to examine the trend on the "black" variable in Table 3, especially spanning from Model 3 to Model 6, as the estimated white-black earnings gap falls from 10.4 percent to 6.6 percent, respectively. As mentioned previously with the lawyer-paralegal example, this demonstrates that, in Model 3, the wage equation misattributed earnings variation to race when it was instead due to differing occupational compositions between whites and blacks. While this may represent another form of discrimination, it is nevertheless vital to recognize that analyses of discrimination that utilize the wage equation produce results that are inherently dependent upon their specification of occupation given the suspected correlation between race and the occupational composition *within* broad vocational groupings.

While all coefficients in the model fluctuate somewhat given the elaboration of occupation between Model 3 and Model 6, another effect to particularly note comes in an examination of the estimated discrimination between whites and Pacific Islanders. In particular, Model 3 indicates a statistically significant effect while a more refined approach to vocation leads to an insignificant coefficient. What makes this finding particularly interesting is that it occurred using a sample of nearly 400,000; given that most efforts in the literature will be working with a drastically smaller sample, the possibility of occupational specification influencing the statistical significance of an outcome grows exponentially. Therefore, wage regressions should take special precaution to examine the robustness of their efforts to the vocational specification utilized in the model.

Occupation-Education Interactions

As discussed earlier, there are a number of reasons that imply occupational-specificity of educational returns, extending from the vocational components of schooling options to the intrinsic productivity (and thus wage) ranges offered by the profession. However, as noted in Freeman and Hirsch (2001) and Sullivan (2005a), typical wage equations inherently assume homogeneity of investment returns across the vocational spectrum by failing to include interactions with occupational controls. While data from the PUMS fails to allow content differences in schooling options, it does allow the potential to examine the vocational specificity to the duration of schooling, an important option given that most data sets express educational attainment only by its length.

Analysis of occupation-education interactions is presented in Table 4, which, for the sake of simplicity, utilizes a set of seven occupational controls interacted with each of the ten educational variables. While Table 4 lists only a portion of those interactions, the individual significance of the presented coefficients pales in comparison to an examination of their joint significance–that is, whether such interactions should be included in the first place. While an F-test on these seventy interactions is indicative of their significance ($F = 36.96$, $p < 0.0001$), an LM test-employed given the large sample size utilized in this study–also is suggestive of the overwhelming significance of including interactions in the model ($LM = 4084.97$, $p < 0.0001$).

In relation to specification of the wage equation, this paper has examined three basic specifications of the wage model in relation to its efforts to control for education and occupation:

Table 3, Models 1-2: $Wage_{ij} = \beta_i * education_i$

Table 3, Models 3-6: $Wage_{ij} = \beta_i * education_i + \alpha_j * occupation_j$

Table 4, Model 7: $Wage_{ij} = \beta_i * education_i + \alpha_j * occupation_j + \gamma_{ij} * interaction_{ij}$

While the first two specifications represent restricted versions of the latter (i.e., $\alpha_j = 0$ and $\gamma_{ij} = 0$), the results in Table 4 demonstrate that such restrictions are misspecifications of the wage model. These findings–combined with the results of Freeman and Hirsch (2001) regarding the significance of occupation-experience interactions–suggest that full specification of the wage model requires that interactions of self-investment and occupation be utilized. Through this relaxation of homogeneity assumptions, the model

TABLE 4. Wage Determination, Males, Full Sample, With Occupation*Education Interactions, Series of Education Dummies

	Model 7			
Education				
Less than 9 years	-0.209 (35.37)			
High school, no diploma	-0.102 (24.61)			
High school diploma	Base			
College: Less than 1 year	0.073 (16.27)			
College: One or more years	0.106 (29.26)			
Associate's Degree	0.134 (26.75)			
Bachelor's Degree	0.222 (40.80)			
Master's Degree	0.310 (23.74)			
Professional Degree	0.113 (4.42)			
Doctorate Degree	0.353 (6.82)			
	Occupation Coefficient	*High School Interaction*	*Associate's Degree Interaction*	*Bachelor's Degree Interaction*
Management Occupations * Education	0.029 (0.77)	0.183 (4.77)	0.179 (4.58)	0.360 (9.37)
Professional & Technical Occupations * Education	-0.058 (0.93)	0.167 (2.67)	0.174 (2.77)	0.273 (4.35)
Blue-Collar Occupations * Education	Base	Base	Base	Base
Clerical Occupations * Education	-0.204 (5.79)	0.184 (5.14)	0.118 (3.18)	0.191 (5.25)
Menial Labor Occupations * Education	-0.247 (12.69)	0.127 (6.28)	0.130 (5.13)	0.071 (2.82)
Personal Services Occupations * Education	-0.141 (1.76)	0.089 (1.09)	0.041 (0.46)	0.065 (0.78)
Sales Occupations * Education	-0.089 (2.57)	0.172 (4.90)	0.185 (5.10)	0.347 (9.80)
R-squared	0.3349			
Adjusted R-squared	0.3346			
Observations	395,244			
F-test on Interactions	36.96 (p<0.0001)			
LM-test on Interactions	4084.97 (p<0.0001)			

Notes: Absolute value of t-statistic in parentheses; model includes the following controls: race, marital status, age, age squared, citizenship status, disability status, state of residence, and industry.

would allow the flexibility required to explore wage determination in a balkanized labor market wrought with short-run disequilibria due to occupational barriers.

DISCUSSION

While the wage equation developed by Mincer (1974) continues to represent a foundation of labor economic analyses, there has nevertheless been an exhibition of nonchalance in the literature regarding the specification of occupation in the model. While data restrictions are often to blame, the results of this paper demonstrate that how one specifies vocation can have subtle, yet significant, influence on research findings. In addition, this paper–along with Freeman and Hirsch (2001)–demonstrates that the implicit assumption of the wage equation regarding homogeneity of returns to human capital across occupations clearly fails. A more detailed examination of wage determination requires the inclusion of occupation-investment interactions.

These issues of occupational specificity in the wage equation have only masked a larger, unresolved ambiguity in the role of vocation from the underlying theory upon which the wage equation was based–the human capital model. Thus, this paper has indicated that refining the basic composition of human capital–beyond general and firm-specific–may provide the necessary theoretical framework upon which to understand some of the labor market phenomena for which it has been criticized in institutionalist literature. In particular, refining human capital to include occupation-specific elements in light of distinct vocational balkanization in the labor market may provide an explanatory framework for the model in regard to sorting models, segmented labor markets, and other phenomenon, thus providing the means to explain and predict the outcomes that have served as the basis for forty years of dissent in certain circles.

While this paper represents a first start at recognizing the broader implications of refined human capital definition, the recent revitalization of work on occupation-specific human capital reveals that much work remains in understanding how occupation and self-investment interact in the labor market to produce various outcomes. The role of occupational specificity permeates such outcomes as wage determination, occupational selection, mobility, turnover, firm investment, and other basic labor market conditions. In particular, understanding the simultaneous nature of wages, education, and occupation–and the aspirations therein-represents a key influence in employment situations that has yet to be fully examined or explained. Further research on these issues may provide further refinements on the human capital framework that will allow researchers a more powerful, sophisticated lens through which to view the labor markets and their outcomes.

Chapter 2

DISPLACED MANUFACTURING WORKERS AND OCCUPATION-SPECIFIC HUMAN CAPITAL

INTRODUCTION

As of January 2006, manufacturing employment in the United States had sunk to its lowest level since 1950, and it has remained relatively flat since a record three-year decline of 2.8 million workers between 2001 and 2003. This rapid deterioration has left an indelible mark on the public consciousness, especially in light of near-daily headlines announcing plant closings at companies once thought to be the foundation of American industry. The concurrent explosion of the service sector as a part of the economy's well-publicized structural transformation has engendered the social myth that laid-off blue-collar manufacturing workers have little option but to retire early, stay in the unemployment line, or end up working at a "big box" retailer. However, despite volumes of research examining post-displacement wage outcomes, scant interest has been directly paid to the occupational outcomes associated with displacement. This lack of attention is surprising given public attention on retraining initiatives undertaken to assuage the inherent mismatch of skills and jobs associated with structural shifts in employment.

At its foundation, understanding occupational movement in the midst of a structural industrial transformation requires an examination of the potential applicability of the knowledge, skills, and abilities (KSAs) utilized by blue-collar workers in the manufacturing industry to other vocations in the labor market. A recently revitalized literature on occupation-specific human capital has particular relevance, as research has begun to demonstrate its importance in determining labor market outcomes (Milgrom 2004; Kambourov and Manovskii 2004a, 2004b, 2005; Sullivan 2005a, 2005b; Groen 2006). This current rejuvenation of occupation-specific human capital literature comes on the heels of two decades during which progress lay dormant following the work by Shaw (1984), who originally proposed such an aspect of human capital by defining *occupational investment* as "the accumulation of skills an individual acquires to perform work within an 'occupation'" (p. 320). Shaw also theorized that occupation-specific skills possessed a certain degree of "transferability" across vocations and across employers. Applying this definition to the plight of displaced workers, one would expect that such individuals would seek to enter occupations in which they could apply-and receive a return on-the greatest percentage of their KSAs; in other words, occupations in which they would have the greatest degree of transferability.

Despite the potential importance of occupation-specific human capital as it relates to labor market outcomes, research to this point has failed to develop an applicable construct to estimate cross-occupation transferability of KSAs. This paper attempts to correct this shortcoming, using data from O*NET to develop a 900 x 900 matrix estimating the transferability of KSAs across occupations. Condensing this into a 500 x 500 matrix capable of matching Census occupational codes, this study utilizes this transferability matrix to examine post-displacement outcomes using the 2004 Displaced

Worker Survey. The results demonstrate that displaced blue-collar workers from the manufacturing industry suffer significantly greater occupation-specific human capital losses than any other labor market group, thereby verifying that the structural shifts in the economy are more prominently harming this sector, as experienced by significantly more pronounced mismatches of skills with available jobs.

Examining occupational movement by laid-off blue-collar workers from the manufacturing industry, this paper will be structured as follows. First, this piece will provide a review of prior literature on post-displacement outcomes, as well as background on the small but growing literature on occupation-specific human capital. Next, this piece will discuss O*NET and the development of the transferability matrix and its potential role in the literature. Finally, the paper will examine occupational outcomes associated with displacement from the manufacturing sector, looking not only at summary trends but also applying the transferability matrix to examine the movement of human capital across vocations upon displacement.

LITERATURE REVIEW

Despite extensive literature on the topic, what defines a "displaced worker" has been a source of contention, given its implications of government responsibility for compensating the losers in structural economic change (Fallick 1996). To build consensus, Jacobson, LaLonde, and Sullivan (2005) identified three common characteristics of most descriptions of displaced workers: "(1) They have not been discharged for cause; (2) they have permanently separated from their former employer or have only a very small likelihood of being recalled to their old jobs; and (3) they have had strong prior attachment to the industry of their pre-displacement employer," (p. 48). Given the importance of workers' strong prior attachment to their pre-displacement job in determining post-displacement outcomes, the Bureau of Labor Statistics typically defines displaced workers as persons having at least three years of tenure upon their permanent job loss.

A majority of the research on displaced workers has focused on earnings losses attributable to displacement, as studies have demonstrated the large and persistent costs that accompany displacement over an individual's work history. The literature suggests that, five years after displacement, earnings typically remain somewhere between 15 and 30 percent lower than a worker's pre-displacement level (among others, Topel 1991; Ruhm 1991; Jacobson, LaLonde, and Sullivan 1993; Schoeni and Dardia 1996; Stevens 1997; Kletzer 1998; Kambourov and Manovskii 2005; Jacobson, LaLonde, and Sullivan 2005).[29] A specific stream of the literature has consistently identified significantly larger earnings losses associated with workers' re-employment attachment to a different industry than that of their former employer (Addison and Portugal 1989; Jacobson, LaLonde, and Sullivan 1993; Carrington 1993; Neal 1995; Parent 2000). While a considerably smaller literature, recent work has also identified similar effects within occupations, as Kambourov and Manovskii (2005) denote that, among males aged twenty to sixty, those switching occupations experienced an 18 percent drop in earnings

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29 For a more extensive review of displaced worker literature, see, among others, Fallick (1996), Kletzer (1998), Farber (2005), and Jacobson, LaLonde, and Sullivan (2005).

compared to a 6 percent decline for those who stayed in their pre-displacement occupation.[30]

The above results have engendered a more sophisticated view of the human capital interpretations of displacement, as some have begun to contend that human capital maintains occupation- and industry-specific aspects that blur the boundaries between "general" and "firm-specific" characteristics. While the recognition of occupational specificity and its influence on the labor market dates back to Adam Smith (1776), Shaw (1984) was the first to apply such principles to the human capital framework. Defining "occupational investment" as the "accumulation of skills an individual acquires to perform work within an 'occupation,'" (p. 320),[31] Shaw suggested that general human capital maintained an occupation-specific component that could be carried across employers. While differing opinions may exist on the potential dissection of human capital into distinct components (as discussed in Chapter 1), the influence of occupation-specific human capital on labor market outcomes has been demonstrated by a growing

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30 Fox (1994) presents the logical explanation, suggesting that earnings drive occupational decisions: if workers can fare better in a different occupation, they are more likely to switch. As such, the idea of "occupational choice" may be a misnomer, given the influence of local labor market environments, resource availability, or other restrictions that dictate a restricted set of outcomes to an individual. Carrington (1993) also examines the role of occupation in earnings losses, however the utilization of one-digit occupational codes represents an overly crude measure that likely conceals significant within-control effects.

31 Shaw (1984) defines an "occupation" as "a homogeneous skill classification within which individuals are perfect substitutes in demand and/or have infinite cross elasticities of substitution in supply. Cabinet-makers and engineers, for example, have occupation-specific skills," (p. 320).

literature (Milgrom 2004; Kambourov and Manovskii 2004a, 2004b, 2005; Sullivan 2005a, 2005b; Groen 2006).[32]

Central to the notion of occupational specificity, Shaw (1984) recognized the importance of transferability in establishing particular labor market outcomes. Distinguishing occupation-specific from firm-specific human capital, Shaw noted that the return to the stock of the former was not completely foregone upon an occupational switch; instead, the return to one's human capital stock depended upon the transferability of skills from one occupation to the next. For instance, the knowledge, skills, and abilities procured through one's time as an accountant may be extremely applicable to becoming an actuary. In contrast, the KSAs acquired during one's time as a dental hygienist may be practically useless as a carpenter. Transferability thereby depends upon the commonality of the KSAs necessary in one occupation as it compares to others across the vocational spectrum; it thus serves a vital role in understanding occupational movement given the varying rates of return of one's acquired skills within different professions.

While cross-occupational transferability of human capital has particular application to occupational choice, retraining initiatives, and a variety of other labor market

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32 It is important to note that while Shaw (1984) established the dominance of occupational investment in determining wages compared to "general" human capital, there has been some issue in regard to the superiority of occupation-specific versus industry-specific human capital. While Kambourov and Manovskii (2004a, 2005) suggest that industry-specific human capital plays little role in wage determination upon the inclusion of occupation-specific human capital in the model, Sullivan (2005a) contends that industry-specific human capital indeed plays a significant role after including within-firm occupational switches. If the former is accurate, however, it begs the question regarding early displaced worker examinations that isolated industrial effects absent occupational concerns were findings of significant effects of industry-switching attributable to a proxy for occupational distribution changes? While this effect of industry-specific human capital is an issue of debate, it should be noted that the role of firm-specific expertise in wage determination has increasingly been established as marginal (Lazear 2003; Kambourov and Manovskii 2004a, 2005; Milgrom 2004; Poletaev and Robinson 2004).

phenomena, research establishing the vocational commonality of characteristics has been limited: Shaw (1984) represents the only known attempt to estimate values of cross-occupation transferability. Shaw proxied such numbers by examining occupational switches, primarily through a retrospective vocational question in the 1970 Census, arguing that there will be greater occupational mobility between jobs that have higher rates of vocational skill transferability. In other words, one would expect to see higher occupational mobility between psychologists and counselors than between psychologists and electricians, given the differences in acquired skills, or variation in applicable occupation-specific human capital.

DEVELOPING NEW INDICES

While Shaw's work laid the foundation for future work on occupation-specific human capital, the use of occupational switching incidence to proxy transferability fails to explicitly examine the knowledge, skills, and abilities actually transferred across occupations, leading to a flawed set of estimates. In other words, while experience as a sports writer may have significant impact on one's productivity as an economics professor through the development of one's writing skills, the lack of *actual* labor market mobility between the two fields would result in an estimated transferability approaching zero using Shaw's method.[33] Thus, given the workings of the labor market and the

[33] Without careful analysis, proxying transferability through occupational switches can ignore the intermediate career steps between vocations. For instance, while there may be transferability between sports writers and economics professors, the occupational switches in the data would reveal non-zero transferability between (a) sports writers and graduate assistants and (b) graduate assistants and professors, but not (c) sports writers and professors. While the solution to this problem would be to, say, multiply the transferability in switch (a) and the transferability in switch (b) to establish the transferability in switch (c),

inherent occupational barriers that restrict mobility (Kerr 1977), the development of cross-occupational transferability estimates would be considerably better served by comparing the actual KSAs utilized within each vocation and developing a corresponding metric based on their applicability across the occupational spectrum.

This paper attempts to rectify this shortcoming in the occupation-specific human capital (OSHC) literature by using data from O*NET, the authoritative national database on vocational information coordinated by the United States Department of Labor. O*NET data characterizes 900 distinct professions along 120 standardized knowledge, skill, and ability categories (listed in Table 5), and is applied in this paper to generate two indices of occupational comparability. The first, t_{ij}, represents an estimated proportion of occupation-specific human capital that would be transferred from one's origin occupation of (occ_i) to one's destination occupation (occ_j). Corresponding to the definition of "transferability" established by Shaw (1984), the estimates of t_{ij} are derived by the computation of a ratio of shared KSAs between two occupations to the KSAs required within the origin occupation. As demonstrated by Shaw (1984), higher rates of transferability, or the ability to apply more of one's acquired OSHC in a new job, should yield higher earnings, all else equal.

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such tactics would be particularly thorny, given the near-infinite career paths available and amount of data needed to estimate such values.

TABLE 5. Knowledge, Skill, and Ability Categories Used by O*NET

Knowledge	*Skill*	*Ability*
Administration and Management	Active Learning	Arm-Hand Steadiness
Biology	Active Listening	Auditory Attention
Building and Construction	Complex Problem Solving	Category Flexibility
Chemistry	Coordination	Control Precision
Clerical	Critical Thinking	Deductive Reasoning
Communications and Media	Equipment Maintenance	Depth Perception
Computers and Electronics	Equipment Selection	Dynamic Flexibility
Customer and Personal Service	Installation	Dynamic Strength
Design	Instructing	Explosive Strength
Economics and Accounting	Judgment and Decision Making	Extent Flexibility
Education and Training	Learning Strategies	Far Vision
Engineering and Technology	Management of Financial Resources	Finger Dexterity
English Language	Management of Material Resources	Flexibility of Closure
Fine Arts	Management of Personnel Resources	Fluency of Ideas
Food Production	Mathematics	Glare Sensitivity
Foreign Language	Monitoring	Gross Body Coordination
Geography	Negotiation	Gross Body Equilibrium
History and Archeology	Operation and Control	Hearing Sensitivity
Law and Government	Operation Monitoring	Inductive Reasoning
Mathematics	Operations Analysis	Information Ordering
Mechanical	Persuasion	Manual Dexterity
Medicine and Dentistry	Programming	Mathematical Reasoning
Personnel and Human Resources	Quality Control Analysis	Memorization
Philosophy and Theology	Reading Comprehension	Multilimb Coordination
Physics	Repairing	Near Vision
Production and Processing	Science	Night Vision
Psychology	Service Orientation	Number Facility
Public Safety and Security	Social Perceptiveness	Oral Comprehension
Sales and Marketing	Speaking	Oral Expression
Sociology and Anthropology	Systems Analysis	Originality
Telecommunications	Systems Evaluation	Perceptual Speed
Therapy and Counseling	Technology Design	Peripheral Vision
Transportation	Time Management	Problem Sensitivity
	Troubleshooting	Rate Control
	Writing	Reaction Time
		Response Orientation
		Selective Attention
		Sound Localization
		Spatial Orientation
		Speech Clarity
		Speech Recognition
		Speed of Closure
		Speed of Limb Movement
		Stamina
		Static Strength
		Time Sharing
		Trunk Strength
		Visual Color Discrimination

TABLE 5. Knowledge, Skill, and Ability Categories Used by O*NET (cont.)

		Visualization
		Wrist-Finger Speed
		Written Comprehension
		Written Expression

The second index established in this paper, q_{ij}, represents a "qualification" rate, or the estimated proportion of occupation-specific human capital required in the destination occupation that can be instilled through work in the origin occupation. A second index is required to understand movement within the labor market because while workers in entry-level occupations may be able to transfer most of their acquired OSHC into higher-order professions (i.e., high transferability), it is an individual's level of qualification that is most important in determining whether an individual secures entry into these higher-order vocations. In other words, while an entry-level retail salesperson may be able to transfer almost all of his or her OSHC into a role as a sales engineer, work in the former vocation alone represents woefully inadequate training for the latter profession, making entry into this higher-order occupation unlikely without further vocational or educational training. Previously ignored in the occupation-specific human capital literature, q_{ij} is estimated as the ratio of shared KSAs between two occupations to the KSAs required within the *destination* occupation.

The derivation of these two occupational indices requires additional explanation of the O*NET data and the methodology involved with creating these measures. In regards to the former, it is necessary to note that O*NET scores the KSAs utilized in each profession along two separate indices: (a) the *level* of each KSA required of one to perform adequately, scored on a 0-7 scale, and (b) the *importance* of each KSA to the responsibilities of the occupation, scored on a 1-5 scale.[34] This two-dimensional approach is important in capturing both the breadth and the depth of KSAs required in each profession. For example, while knowledge of "Medicine and Dentistry" may be equally important to the duties of a paramedic and a physician, the level of such knowledge required is vastly different across the two professions.[35] Therefore, as a means of consolidating the two scores into a meaningful, unitary metric within each KSA category for a given occupation (necessary for future steps), this paper advances the use of δ_{im}, or the product of the importance and level scores for each KSA dimension, *m*, within each occupation, *i*. By weighting the importance of a KSA by its level, this step generates a "point" total encapsulating the breadth and depth of that characteristic within an occupation. This produces 120 values of δ_{im} for each occupation, one for each of the 33 knowledge, 35 skill, and 52 ability categories employed by O*NET to characterize each vocation. Ranging from 0-35,[36] δ_{im} "point" totals within knowledge categories for human resource managers, for example, include: administration and management

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34 While O*NET lists the level and importance of each KSA on a 100-point scale in the on-line version, this represents a mere transformation of the developer format that scores data on a 0-7 (level) and 1-5 (importance) scale. Note that these scales are not restricted to integers; for example, the score for a level may be 5.16.

35 As an opposing example, consider writing skills for psychology professors and newspaper reporters. While the two occupations may require similar *levels* of expertise, the *importance* of writing across the two vocations is quite different. While the reporter's entire job may revolve around his or her writing skill, psychology professors may succeed through the utilization of other skills, such as instructing students, providing counseling services, and organizing research projects.

36 The maximum is rarely met in a specific category, as only selected occupation-KSA categories are scored at 35 (e.g., surgeons and knowledge of medicine and dentistry).

(21.735), biology (0.000), clerical (5.033), personnel and human resources (30.800), and telecommunications (1.538).

Upon computing each of the 120 δ_{im} values for all 900 occupations scored by O*NET, the next step is to make pair-wise comparisons of δ_{im} values across vocations in order to establish the number of shared KSA "points" between two occupations; this value represents the numerator in the computation of both t_{ij} and q_{ij}. This process is demonstrated in Table 6, as four of the δ_{im} knowledge scores are compared across two occupations: economist (occ_i) and human resources manager (occ_j). Looking within the "Computers and Electronics" category, economists use 8.84 points while human resources managers utilize 5.00 points. Within this standardized category, it can be deduced that the two occupations "share" 5.00 points; while HR managers can apply all 5.00 of their points in their role as an economist, given that it requires greater knowledge in that category, economists can apply only a portion of their 8.84 points as an HR manager, given the latter's more limited requirements. As a result, defining ϕ_{ijm} as the shared point total between occupations *i* and *j* within a given KSA dimension, *m*, the formula becomes:

(1) $\phi_{ijm} = \min(\delta_{im}, \delta_{jm})$

TABLE 6. Comparing δ_{im} Scores to Establish Applicability of Required KSAs

	δ_{im} *Scores*			
Occupation (SOC)	*Computers & Electronics*	*Personnel & Human Resources*	*Communications & Media*	*Economics & Accounting*
i: Economist (19-3011.00)	8.84	6.72	3.24	24.64
j: Human Resources Manager (11-3040.00)	5.00	30.80	3.87	6.20
Shared Point Value	5.00	6.72	3.24	6.20

Upon the calculation of the 120 ϕ_{ijm} values for each ij occupation combination, this paper first turns its attention to the derivation of t_{ij}, the first metric described above estimating transferability, or the proportion of OSHC from one's origin vocation that can be applied in one's destination occupation. This value is estimated by the ratio of the number of shared points between occupations *i* and *j* to the total number of points within the origin occupation *i*. While the direct summation of each value would assume equal weighting between the 120 KSA categories, this paper advances a slight variation, instead giving equal weight to the knowledge, skill, and ability categories as a whole considering the unequal number of dimensions scored within each category by O*NET:[37]

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37 As of June 2006, version 9.0 represented the latest release of O*NET data. However, upon comparing data across occupations, it became clear that there were nonsensical, systematic outcomes that derived from working with this data; for example, upon summing δ_{im} scores, version 9.0 data listed "steamfitters" as the occupation requiring the most knowledge across the 900 occupational categories used to define the labor market, higher than such vocations as physicists and physicians. Considering that this represented one of many nonsensical results, this paper utilizes O*NET version 4.0, which solely applies expert analysis of occupational characteristics. While no known paper has outlined the reasoning behind such inconsistencies across occupations in O*NET's later versions, the likely cause lies with the data collection process underlying O*NET. In particular, to update their data-a key feature of the system as advertised by O*NET itself-O*NET surveys a random sample of workers within given occupations to produce "updated" numbers regarding the level and importance of specific knowledge, skills, and abilities within the given vocation. However, given that the developer version of O*NET 7.0 shows update sample sizes of fifteen to

$$(2) \quad t_{ij} = avg\left(\frac{\sum_{k=1}^{33} \phi_{ijk}}{\sum_{k=1}^{33} \delta_{ik}}, \frac{\sum_{s=1}^{35} \phi_{ijs}}{\sum_{s=1}^{35} \delta_{is}}, \frac{\sum_{a=1}^{52} \phi_{ija}}{\sum_{a=1}^{52} \delta_{ia}} \right)$$

To understand how this works, consider the abbreviated example in Table 7, which revisits the four knowledge scores (δ_{im}) for two occupations-economists and human resources managers. With the sum of shared points (21.16) between the two vocations serving as the numerator (ϕ_{ijm}) and the total points of the origin occupation (43.44) serving as the denominator (δ_{im}), the resulting value represents the percent of KSAs that would be transferable from one occupation to the next, or t_{ij}=0.4871. By summing this within all knowledge, skill, and ability categories, and then averaging the totals to provide equal weighting, the resulting value represents the estimated proportion of OSHC transferability as pursued by Shaw (1984).

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thirty within each occupation to serve as the means of updating specific vocational totals, it very well could be that small sample sizes are creating hidden, yet substantial, inconsistencies in the comparison of characteristics across occupations. Further investigation of the causes of these nonsensical outcomes would represent a significant boon to researchers, practitioners, and developers.

TABLE 7. Demonstrating the Development of Transferability Scores

	δ_{im} Scores						
Occupation (SOC)	*Computers & Electronics*	*Personnel & Human Resources*	*Communi-cations & Media*	*Economics & Accounting*	*Sum* (δ_{im})	*Sum* (ϕ_{ijm})	$t_{ij} = \phi_{ijm} / \delta_{im}$
i: Economist (19-3011.00)	8.84	6.72	3.24	24.64	43.44		
j: Human Resources Manager (11-3040.00)	5.00	30.80	3.87	6.20	45.87		
Shared Point Value (ϕ_{ijm})	5.00	6.72	3.24	6.20		21.16	0.4871

While the preceding example represents an examination of two occupations and four KSA dimensions, it should be noted that the full expansion of the model produces a 900 x 900 matrix of transferability scores, T. While this matrix is too cumbersome to be presented in its entirety within this paper,[38] Table 8 advances a 5 x 5 snippet of T in order to provide some clarity on the structure of the larger matrix. As an example, t_{15} suggests that only 7.72 percent of the KSAs utilized by a government service executive (occ_1) can be applied to one's position as a refuse and recyclable material collector (occ_5). Similarly, t_{24} indicates that 18.39 percent of the KSAs utilized by an industrial production manager (occ_2) can be applied to work performed by a bread and pastry bakers (occ_4). Conversely, t_{42} suggests that 96.48 percent of the KSAs used by a bread

38 The full matrix is available in electronic form from the author.

TABLE 8. 5x5 Fragment of T, the KSA Transferability Matrix (Values Represent t_{ij})

	Occupation i (SOC Codes)				
Occupation j (SOC Codes)	*11-1011.01*	*11-3051.00*	*43-3061.00*	*51-3011.01*	*53-7081.00*
11-1011.01	1.0000	0.7889	0.9150	0.7457	0.5986
11-3051.00	0.6771	1.0000	0.9004	0.9648	0.8390
43-3061.00	0.3274	0.4038	1.0000	0.6910	0.5564
51-3011.01	0.1265	0.1839	0.3147	1.0000	0.5498
53-7081.00	0.0772	0.1236	0.1906	0.4125	1.0000

Note: Occupational titles are as follows: government service executives (11-1011.01); industrial production managers (11-3051.00); procurement clerks (43-3061.00); bakers, bread and pastry (51-3011.01); and refuse and recyclable material collectors (53-7081.00).

and pastry baker can be applied to work as an industrial production manager. It is important to note that, while t_{24} and t_{42} have the same numerator (shared points), the denominators (total points within the origin occupation) differ. Thus, considering that industrial production manager jobs are more demanding than baker positions (and thus have a larger denominator), t_{24} does not equal t_{42}; this mirrors the larger trend that t_{ij} does not equal t_{ji}, thereby accounting for the lack of symmetry in the matrix. Table 8 is shaded along the diagonal to reinforce this asymmetry.

The derivation of the qualification rate, q_{ij}, represents a slight variation from the computation of the transferability rate, t_{ij}. While the two values maintain the same numerator-the shared point value between occupations *i* and *j*-the denominator of the qualification rate is the total point value of the *destination* occupation, j. Therefore, the formula for the qualification rate, can be represented as follows:

$$(3) \quad q_{ij} = avg\left(\frac{\sum_{k=1}^{33} \phi_{ijk}}{\sum_{k=1}^{33} \delta_{jk}}, \frac{\sum_{s=1}^{35} \phi_{ijs}}{\sum_{s=1}^{35} \delta_{js}}, \frac{\sum_{a=1}^{52} \phi_{ija}}{\sum_{a=1}^{52} \delta_{ja}} \right)$$

Just as with the transferability rates, the development of qualification rates produces a 900 x 900 matrix for each occupational pair-wise combination. This qualification matrix, Q, provides the degree to which work in occupation *i* prepares one for work in occupation *j* across the entire vocational spectrum. However, given the definition of each q_{ij} comprising the matrix, it is important to note the following:

$$(4) \quad q_{ij} = t_{ji}$$

This follows from the fact that both terms, by definition, use the same numerator (shared KSA points between occupations *i* and *j*) and denominator (total KSA points in occupation *j*). Therefore, generalizing this to matrices created, Q is the transpose of T, or:

$$(5) \quad Q' = T$$

TABLE 9. 5x5 Fragment of Occupational Matrix, Presenting Q_{ij} and T_{ij}

	Occupation T_i and Q_j (Across)				
Occupation T_j and Q_i (Down)	*11-1011.01*	*11-3051.00*	*43-3061.00*	*51-3011.01*	*53-7081.00*
11-1011.01	1.0000	0.7889	0.9150	0.7457	0.5986
11-3051.00	0.6771	1.0000	0.9004	0.9648	0.8390
43-3061.00	0.3274	0.4038	1.0000	0.6910	0.5564
51-3011.01	0.1265	0.1839	0.3147	1.0000	0.5498
53-7081.00	0.0772	0.1236	0.1906	0.4125	1.0000

Note: Occupational titles are as follows: government service executives (11-1011.01); industrial production managers (11-3051.00); procurement clerks (43-3061.00); bakers, bread and pastry (51-3011.01); and refuse and recyclable material collectors (53-7081.00).

To help explain this, Table 9 re-examines the 5 x 5 snippet of the matrix presented in Table 8. This version allows one to access the qualification and transferability rates between any two occupations *i* and *j*. To interpret this table, one can find the appropriate t_{ij} by locating the column containing occupation *i* across the top of the table and then moving down the matrix to find the row housing occupation *j*; similarly, one can determine q_{ij} by finding the row of occupation *i* down the side of the table and then moving across the matrix to locate the column containing occupation *j*. For instance, if one wants to know t_{13}, or the transferability rate of OSHC from government service executives (occ_1) to procurement clerks (occ_3), the appropriate number is found by moving over to the first column and then down to the third row to note that 32.74 percent of the KSAs used in the former occupation are applicable in the latter occupation. Conversely, if one wants to find q_{13}, or how much working as a government service executive "qualifies" one to work as a procurement clerk, the result is found by looking at the first row and following it to the third column to denote that a government service executive utilizes 91.50 percent of the skills required of a procurement clerk.

To recap, this paper represents the first known attempt to develop a full OSHC transferability matrix based on occupational characteristics and introduces the concept of a qualification rate while generating a similar matrix. Using data from O*NET, this paper generates a 900 x 900 matrix that makes pair-wise comparisons of the KSAs used within each vocation to estimate the two occupational indices. While an imperfect estimator of occupational comparability, it nevertheless represents a significant advancement in understanding occupational movement in the labor market and is a tool that will be utilized in later sections to examine the effects of structural unemployment.[39]

DATA AND MODEL

This investigation of post-displacement occupational outcomes utilizes data drawn from 1984-2004 Displaced Worker Surveys (DWS), a supplement to the January edition of the Current Population Survey (CPS) in even-numbered years. Displaced workers are identified through a question in the CPS that asks, "During the last three calendar years...

39 Using data on occupational characteristics to estimate transferability requires a number of caveats. First, this effort ignores occupational barriers that would prohibit the direct transfer of KSAs between two particular vocations. For instance, while it is estimated that 71.1 percent of the KSAs applied by kindergarten teachers can be utilized in one's job as a pediatrician, there are educational barriers (i.e., a medical degree) that would prohibit occupational mobility from the former to the latter in the absence of such schooling. Second, it is important to note that applying aggregate occupational requirements to study individual occupational movement implicitly fails to capture potential differences of individuals' actual KSAs *within* occupations. For instance, a master electrician would stand to lose significantly more rent to his or her accumulated occupation-specific human capital compared to an apprentice. Finally, the development of the transferability/qualification matrix fails to include specific work activities or other potential occupation-specific features that might also influence the estimates.

did (you) lose a job or leave one because: (your) plant or company closed or moved, (your) position or shift was abolished, there was insufficient work, or another similar reason?"[40] If the respondent replies "yes" to that question, he or she is asked a series of questions regarding the lost job, including some information on the reason for the person's displacement, as well as a series of questions regarding his or her prior job, including his or her tenure, union status, full-time status, earnings, and so on. This data is obtained in addition to details on the respondent's current job, earnings, and demographic information as acquired through the main CPS survey tool.

While the DWS represents the "industry standard" (Seitchik 1991, 51) for studying displacement, given its overwhelming strengths, namely its large, random sampling of U.S. households weighted to represent the country's workforce, it is important to note the potential biases attributable to utilizing this data. First, research has suggested that the DWS significantly understates the number of displaced workers due to its "snapshot" nature (Kletzer 1998) and its failure to collect information on multiple job losses (Stevens 1997). In addition, studies have suggested that retrospective biases may further understate the number of displaced workers over the preceding five-year period by approximately one-third, and may not be randomly distributed across groups (Evans and Leighton 1995).[41] Finally, as noted by Kambourov and Manovskii (2004b), there are significant

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[40] Prior to 1996, the DWS had a five-year recall period. For example, the 1992 DWS asked respondents if they had been displaced at any time in 1987-1991. There is a slight discontinuity in the definition of displaced worker in this study from 1984 to 1992 and 1994 to 2004, as earlier surveys failed to inquire whether a person was expecting recall from his or her displaced job. Under current BLS definitions, those individuals would not be considered "displaced."

[41] For more discussion on the retrospective biases of the DWS, see Topel (1991), Farber (1993, 1997), Fairlie and Kletzer (1996), and Kletzer (1998), among others.

coding errors attributable to occupation within the Current Population Survey that may hinder studies of occupational mobility. While the imputation of occupation by coders exists, those observations represented less than 1 percent of the current sample and were subsequently dropped from this analysis.

Caveats aside, given that the questions at hand focus on those displaced from blue-collar occupations in the manufacturing industry, this study identifies "blue-collar" vocations as those in the following occupational categories: transportation and material moving; production; installation, maintenance, and repair; construction and extraction; and farming, fishing, and forestry. Restricting the sample to those aged twenty and older, Table 10 provides means for the resulting data drawn from the 2004 DWS. As exhibited in the table, much of the current stereotype of displaced blue-collar manufacturing workers is accurate, namely that they are typically predominantly male, older, less educated, more likely to be a union member, and more concentrated in the Midwest when compared to the entire set of displaced workers across all industries and occupations. These results are unsurprising, as they are consistent with the findings of Kletzer (2001).

This study will utilize a two-pronged approach to examine the occupational outcomes of displaced blue-collar manufacturing workers. First, considering that vocational outcomes of displacement largely have been ignored in the literature, this study will begin by providing summary trends of occupational movement over the twenty-year period in question. To investigate the potential causal factors of the occupational placement of those displaced from blue-collar manufacturing positions, this paper then applies a

TABLE 10. Comparison of Blue-Collar Manufacturing Displaced Against Other Displaced, 2004 Displaced Worker Survey

	All Displaced	*Displaced Blue-Collar*	*Displaced Manufacturing*	*Displaced Blue-collar manufacturing*
Male	0.554	0.788	0.634	0.658
Age	40.82	40.30	43.17	42.55
Married	0.556	0.572	0.599	0.572
# of Children, Age<18	0.709	0.773	0.702	0.732
Education				
No HS Diploma	0.111	0.211	0.144	0.207
HS Graduate, No College	0.319	0.443	0.393	0.493
Some College, No Degree	0.215	0.199	0.177	0.166
Assoc. or Voc. Degree	0.087	0.082	0.078	0.069
Bachelor's Degree	0.198	0.056	0.170	0.058
Graduate Degree	0.070	0.009	0.037	0.006
Race				
White	0.831	0.853	0.824	0.808
Black	0.097	0.101	0.101	0.128
Other	0.051	0.046	0.064	0.064
Region				
Northeast	0.217	0.191	0.252	0.229
Midwest	0.247	0.255	0.270	0.291
South	0.256	0.275	0.257	0.284
West	0.281	0.279	0.220	0.196
City Status				
Central City	0.240	0.210	0.208	0.197
Balance of City	0.416	0.365	0.405	0.357
Non-Metro	0.190	0.266	0.231	0.290
Other	0.154	0.160	0.154	0.156
Union Member	0.087	0.185	0.148	0.219
Citizen	0.934	0.904	0.927	0.909
Veteran	0.099	0.141	0.127	0.131
Received UI Benefits	0.494	0.541	0.651	0.663
Exhausted UI Benefits	0.219	0.239	0.313	0.322
Observations	4,774	1,566	1,162	704

variant of the nested logit model of occupational choice originally advanced by Soopramanien and Johnes (2001). The choice structure demonstrated in Figure 2 represents an improvement on standard multinomial logit models (Schmidt and Strauss 1975), as it allows for non-employment options that are prevalent among displaced workers (15.1 percent of the 2004 DWS sample) and must be considered in any study of the employment status of displaced workers.[42] The nested logit structure utilized in this study advances a two-stage decision process; first, the respondent "chooses" an employment outcome (employed, not employed, not in the labor force) before selecting an occupation conditional on choosing employment. With six occupational categories, the nested logit model is estimated using a standard battery of demographic variables allowed by the CPS-age, tenure, race, marital status, number of children, union membership, citizenship status, education, region, city status, notice of layoff, and unemployment insurance status. The model is estimated for males within a pooled data set extending from 2000 to 2004 to obtain a suitable sample size while attempting to minimize across-year differences in the labor market.[43]

The second avenue pursued in this piece will address the relationship between occupation-specific human capital and vocational outcomes following displacement. In

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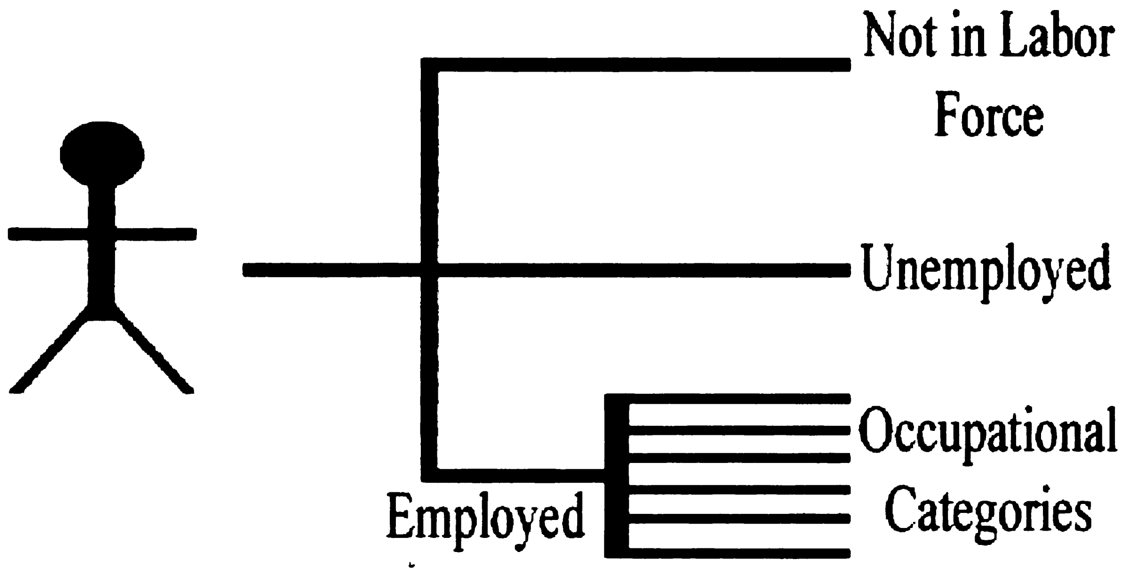
42 Attempts to include non-employment as an outcome of a multinomial logit (MNL) model of occupational choice impose an unrealistic choice structure on the respondent. Further, merely including non-employment outcomes in a MNL structure runs the risk of violating the independence of irrelevant alternatives (IIA) assumption necessary for the proper estimation of MNL models, which implies that adding another alternative or changing the characteristics of a third alternative does not affect the relative odds between two alternatives within the available set of choices. For a further discussion of the IIA assumption, see Wooldridge (2001) or the classic "red bus, blue bus" example.

43 The nested logit model is estimated separately by gender given documented differences in labor market behavior (see, among others: Oaxaca, 1973; MacPherson and Hirsch, 1995; Soopramanien and Johnes 2001). The results for females between 2000 and 2004 are given in Appendix B and are not highlighted in the text due to the significantly smaller sample size.

particular, this analysis examines two hypotheses. First, manufacturing shed 2.8 million workers in the three-year span between 2001 and 2003, the largest such decline in the industry since the BLS began recording industry employment in 1939 and *a priori* evidence of a structural economic shift away from blue-collar manufacturing work in the United States. Displaced workers from this sector should experience this structural shift by a greater mismatch of skills to available jobs when compared to those displaced from other segments of the labor force. This should produce lower re-employment rates following displacement among displaced blue-collar manufacturing workers, as well as lower degrees of transferability of knowledge, skills, and abilities from their previous job upon finding employment. These hypotheses can be tested using data from the 2004 DWS (covering those displaced between 2001 and 2003) and the transferability matrix as a means of confirming and examining the effects of the structural economic shift on those displaced from blue-collar manufacturing jobs.

FIGURE 2. Diagram of Hierarchical Decision Tree Applied by Nested Logit Model of Occupational Choice



Corresponding to vocational outcomes, this paper will also examine the wage impact of occupation-specific human capital within the displaced worker framework. Human capital theory suggests that capturing more of one's specific human capital following displacement should result in a higher wage. Thus, using the transferability matrix described in this paper, one would expect that those experiencing higher degrees of transferability of acquired KSAs from their lost job should exhibit higher wage rates, *ceteris paribus*. In essence, this becomes a test of the theoretical underpinnings of occupation-specific human capital and the transferability matrix employed in this paper. Given a change in occupational coding structure and differing economic environments across years, this examination will also be limited to data from the 2004 DWS.

RESULTS

Table 11 provides a summary of occupational outcomes for displaced blue-collar manufacturing workers from 1984 to 2004 who were re-employed at the time of the survey, offering a number of interesting trends despite the use of broad occupational classifications.[44] Most significantly, rates of re-employment within the blue-collar segment of the occupational spectrum have declined; while roughly 67-70 percent of displaced blue-collar manufacturing workers were re-employed in blue-collar jobs from 1984 to 2000, that percentage had fallen to 64 percent in the 2002 and 2004 DWS. Much lower rates of re-employment in blue-collar manufacturing jobs have fueled much of this

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44 The 2004 CPS (and DWS) utilizes a different occupational coding structure than previous years. Because of this, Table 11 utilizes broad vocational categorization in order to provide cross-year consistency in occupational definition.

TABLE 11. Re-Employment Occupation of Displaced Blue-Collar Manufacturing Workers, 1984-2004 DWS

	1984	*1986*	*1988*	*1990*	*1992*	*1994*	*1996*	*1998*	*2000*	*2002*	*2004*
Executive, Administrative, and Managerial	3.0%	3.2%	4.1%	3.2%	2.4%	2.9%	2.9%	2.7%	3.3%	2.8%	3.2%
Professional Specialty	2.4%	1.4%	2.4%	2.4%	1.6%	3.1%	2.9%	2.4%	1.7%	3.3%	4.8%
Technicians and Related Support	1.5%	1.8%	0.5%	1.7%	1.4%	2.2%	0.9%	1.4%	1.7%	2.0%	1.4%
Sales	5.4%	5.9%	5.3%	5.7%	6.8%	6.0%	5.0%	5.8%	2.7%	9.2%	5.1%
Administrative Support Including Clerical	6.6%	6.6%	6.7%	5.4%	6.2%	8.0%	6.7%	6.9%	9.0%	4.9%	9.1%
Protective Service	1.6%	1.4%	2.2%	2.3%	1.6%	1.1%	0.9%	1.0%	1.0%	2.0%	1.8%
Service, Except Protective	11.2%	12.8%	9.8%	9.0%	13.3%	8.0%	10.2%	10.3%	9.7%	11.7%	10.3%
Blue-Collar Occupations	68.3%	67.0%	69.2%	70.4%	66.7%	68.6%	70.5%	69.5%	70.9%	64.1%	64.2%
Blue-Collar Occupations – Manufacturing	39.3%	41.6%	45.3%	47.5%	46.3%	49.8%	48.1%	46.9%	45.2%	35.0%	38.8%
Blue-Collar Occupations – Non-Manufacturing	29.0%	25.3%	23.9%	22.9%	20.4%	18.8%	22.4%	22.6%	25.8%	29.1%	25.5%
Observations (Employed)	1,272	1,235	837	756	795	448	343	292	299	392	436
Observations (Unemployed)	892	727	406	356	582	295	177	125	119	335	294
Observations (Total)	2,164	1,962	1,243	1,112	1,377	743	520	417	418	727	730
Re-Employment Rate	58.8%	63.0%	67.3%	68.0%	57.7%	60.3%	66.0%	70.0%	71.5%	53.9%	59.7%

trend, as just 38.8 percent of those displaced from such jobs between 2001 and 2003 were re-employed in blue-collar manufacturing positions. While such re-employment and industry absorption rates follow economy-wide and industry expansion/contraction cycles, respectively, the figures post-2000 represent significant downturns.

While the results of Table 11 may offer initial evidence of a quickening of structural change in the economy away from blue-collar employment, the volatility of other sectors makes it difficult to necessarily pinpoint growth areas. Sales and service occupations, in particular, have not demonstrated increased absorption rates of displaced blue-collar manufacturing workers over the last two decades, standing contrary to the social myth regarding such individuals landing as burger flippers or stock handlers at big-box retailers. On the contrary, administrative support and professional specialty occupations have seen general increases in their absorption rates of displaced workers from this sector. These results may be marginally indicative of retraining success, the expansion of particular segments of the labor market, or a combination of other factors.

The causal influences of this occupational choice are examined in Table 12 through the estimation of the nested logit model. While the coefficients are not directly interpretable and thus take on the role of an index of dissimilarity (Greene 2002), the results indicate that having a college degree represents a statistically significant feature of those entering

TABLE 12. Nested Logit Results, Displaced Blue-Collar Manufacturing Workers, Males, 2000-2004 DWS

	Participation Choice (Branch)		*Occupational Choice (Twig)*				
	Unem-ployed	*NILF*	*Profession-al, Manage-ment*	*Service*	*Sales*	*Clerical*	*Blue-Collar, Non-Man.*
Age							
20-24	-0.149 (0.340)	-0.481 (0.447)	-1.061* (0.572)	0.090 (0.470)	-0.627 (0.717)	-0.097 (0.683)	0.479 (0.348)
25-34	-0.065 (0.223)	-0.653** (0.327)	-0.840** (0.354)	-0.625 (0.392)	-0.145 (0.444)	-0.207 (0.532)	-0.091 (0.245)
35-44	Base	Base	Base	Base	Base	Base	Base
45-54	0.363 (0.237)	-0.061 (0.309)	-0.881** (0.400)	0.249 (0.399)	-0.451 (0.514)	-0.185 (0.549)	-0.096 (0.276)
55=64	0.490 (0.310)	0.823** (0.359)	-0.485 (0.546)	0.317 (0.530)	*	-1.864 (1.141)	-0.305 (0.380)
65 & up	0.564 (0.778)	2.225*** (0.690)	-0.142 (1.306)	0.710 (1.289)	*	0.352 (1.392)	0.723 (0.906)
Job Tenure	-0.009 (0.011)	0.013 (0.012)	-0.014 (0.022)	-0.040* (0.024)	0.019 (0.025)	0.033 (0.023)	0.010 (0.012)
Race							
Black	0.160 (0.292)	0.154 (0.359)	-0.531 (0.554)	-0.301 (0.555)	-0.768 (0.806)	0.028 (0.833)	-0.224 (0.340)
Other	0.148 (0.356)	0.654 (0.418)	-0.316 (0.577)	-0.417 (0.611)	*	0.919 (0.619)	-1.370** (0.582)
Married	-0.383* (0.198)	-0.521** (0.250)	-0.410 (0.332)	-0.750** (0.337)	-0.386 (0.433)	-0.052 (0.475)	-0.277 (0.233)
Children <18	-0.060 (0.085)	-0.193 (0.126)	-0.044 (0.140)	0.024 (0.139)	-0.374* (0.222)	-0.506** (0.257)	0.000 (0.094)
Union, Old Job	0.133 (0.206)	0.533** (0.251)	-0.804** (0.389)	-0.044 (0.377)	-0.841 (0.519)	-0.394 (0.542)	-0.054 (0.232)
US Citizen	0.016 (0.272)	-0.012 (0.341)	-0.289 (0.384)	-0.455 (0.387)	-1.250** (0.488)	-0.863* (0.510)	-0.229 (0.288)
Education							
Less than HS	0.502** (0.243)	-0.190 (0.325)	-0.228 (0.495)	0.598 (0.377)	-0.521 (0.673)	-0.203 (0.678)	0.572** (0.261)
HS Diploma	Base	Base	Base	Base	Base	Base	Base
Some College	0.160 (0.230)	0.124 (0.286)	0.829** (0.363)	0.428 (0.366)	0.164 (0.522)	0.597 (0.492)	0.168 (0.257)
Vocational or Assoc. Deg.	-0.333 (0.399)	-0.088 (0.448)	1.600*** (0.448)	-0.057 (0.675)	1.243** (0.572)	0.300 (0.825)	0.711** (0.356)
College Deg.	0.553 (0.388)	0.148 (0.503)	2.027*** (0.485)	0.993* (0.568)	1.235* (0.639)	0.604 (0.780)	0.142 (0.477)
Region							
Northeast	-0.254 (0.252)	-0.757** (0.325)	-0.619 (0.404)	-0.702 (0.456)	-0.353 (0.584)	-1.532** (0.646)	-0.048 (0.298)
Midwest	-0.069 (0.238)	-0.640** (0.303)	-0.782* (0.402)	0.182 (0.374)	0.393 (0.507)	-0.683 (0.505)	0.180 (0.281)
South	-0.202 (0.252)	-0.430 (0.310)	-0.357 (0.383)	-0.162 (0.416)	0.061 (0.547)	-1.448** (0.618)	0.222 (0.290)

TABLE 12. Nested Logit Results, Displaced Blue-Collar Manufacturing Workers, Males, 2000-2004 DWS (cont.)

West	Base	Base	Base	Base	Base	Base	Base
City Status							
In City	-0.189 (0.240)	-0.373 (0.301)	-0.369 (0.415)	-0.124 (0.393)	-0.279 (0.518)	-0.899 (0.600)	-0.181 (0.277)
Balance of City	-0.137 (0.201)	-0.659** (0.260)	-0.112 (0.346)	0.140 (0.327)	0.046 (0.434)	-0.234 (0.463)	-0.082 (0.227)
Non-Metro	Base	Base	Base	Base	Base	Base	Base
Other	-0.367 (0.262)	-0.414 (0.319)	0.548 (0.401)	-0.863 (0.547)	-0.126 (0.592)	-0.173 (0.640)	-0.088 (0.286)
Notice of Layoff	-0.175 (0.172)	-0.245 (0.221)	0.194 (0.281)	-0.437 (0.302)	-0.079 (0.380)	-0.220 (0.413)	0.125 (0.193)
UI Exhaustee	0.452** (0.199)	0.451* (0.244)	0.304 (0.334)	0.005 (0.366)	0.414 (0.442)	0.364 (0.489)	0.354 (0.230)
Inclusive Values	Em-ployed	0.6707	Unem-ployed	0.5000	NILF	0.5000	
Observations	1,100						
Log-likelihood	-1,880.3354						
LR chi2(169)	814.1007						
Prob > chi2	0.0000						

Note: Standard error in parentheses.

professional/management and sales occupations following displacement. Beyond the role of education, the model also serves to confirm a number of common beliefs, namely that older males are considerably more likely to drop out of the labor force and married men exhibit significantly higher rates of not only staying in the labor market but also finding a job.[45]

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45 A comparison of multinomial logit and nested logit procedures encompassing the eight possible outcomes (six occupations, unemployment, nonparticipation) yields statistically significant evidence verifying the latter's dominance in modeling occupational choice. As noted in Soopramanien and Johnes (2001), the test statistic comparing the two models, $-2(LR_m - LR_n)$, is distributed as a χ-square with the degrees of freedom equaling the number of restrictions that are imposed in order to reduce the nested logit to a simple multinomial logit (results of the multinomial logit model are available from the author upon request). Therefore, with the current models yielding a test statistic of 18.0329, the results of this study indicate the preference for utilizing nested logit procedures when working with occupational choice of

While results of the preceding occupational analyses have only indirectly spoken to structural effects in the economy, a more direct approach recognizes that within a structural shift in the economy, those displaced from occupations deemed most vulnerable would find fewer openings in comparable professions. Those displaced from these segments of the labor market would be expected to be forced to accept positions utilizing less of their acquired occupation-specific human capital, given its relative obsolescence when applied to expanding portions of the labor market. When translated through the lens of the transferability matrix developed earlier in this study, the supposed effects of economic restructuring on the hypothesized group in question-blue-collar manufacturing workers-should be demonstrated by those displaced from this segment applying lower percentages of the KSAs acquired in their pre-displacement vocation to their post-displacement occupation. Therefore, a direct examination of structural effects on blue-collar manufacturing workers leads the analysis to apply a condensed,[46] 500 x 500 version of the transferability matrix (to match the DWS occupational coding structure) to data from the 2004 DWS that captured a time of great upheaval in the

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displaced workers. Thus, while this study employs only a rudimentary set of explanatory variables, which, outside of age and education, have little theoretical implications for the labor market outcomes of displaced workers, the results of this study indicate that occupational choice models incorporating more advanced data (such as retraining initiatives) would be well advised to apply nested logit to more accurately model the decision-making process.

46 By far, the most prevalent inconsistency between the occupational structure of the DWS/Census and the SOC was that of multiple SOC codes matching onto one DWS/Census vocational code. To alleviate this problem, the γ_{ij} are averaged over all matching SOC codes to generate the appropriate DWS/Census γ_{ij}. While this technique has been utilized by those working with O*NET data (Hirsch 2005), one must be wary of the effects of averaging SOC classifications that have grossly unequal number of job holders. For instance, the matrix scores for the DWS/Census occupation code of "Chief Executives (0010)" represents the average of matrix scores for the SOC occupation codes for "Government Service Executives (11-1011.01)" and "Private Sector Executives (11-1011.02)." While the number of individuals holding such jobs are not likely to be equal across the economy, methods that utilize averaging are inherently producing biased results. However, the absence of detailed statistics on the number of job holders by SOC/O*NET occupational categories mandates the continued utilization of cross-SOC averages in order to merge O*NET data with Census survey data.

TABLE 13. Transferability of KSAs, Displaced Blue-Collar Manufacturing Versus All Other Displaced, 2004 DWS

	Obs.	*Pct. Employed*	γ_{ij}: *Transfer*	γ_{ij}: *Qualified*
Displaced, Overall				
Blue-Collar Occupations, Manufacturing	345	60.80%	68.01%	71.19%
All Other Displaced	2481	67.99%	75.36%	76.78%
t-Statistic			5.852	4.637
Displaced, By Sector				
Professional/Technical Occupations	893	71.18%	74.28%	82.45%
Service Occupations	283	61.12%	75.11%	72.46%
Sales Occupations	294	68.39%	74.02%	73.52%
Clerical Occupations	435	64.81%	75.31%	70.93%
Blue-Collar Occupations, Manufacturing	345	60.80%	68.01%	71.19%
Blue-Collar Occupations, Non-Manufacturing	574	69.54%	77.95%	76.26%

manufacturing industry, namely those displaced from that sector between 2001 and 2003.[47]

The results of applying the transferability matrix to data from the 2004 DWS are posted in Table 13, and are distinctly illustrative of the structural obsolescence of blue-collar occupations within the manufacturing industry. In addition to lower re-employment rates, those displaced from this sector exhibit a significantly lower percentage of transferability (68.01 percent) of their knowledge, skills, and abilities to their post-displacement occupation than those displaced from the balance of the labor market (75.36 percent). Comparing sectors in the bottom half of Table 13 further reinforces this conclusion, as all other categories of workers exhibit transfer rates over 74 percent, far exceeding the rates

47 The condensing of SOC/O*NET occupational classifications to DWS/Census codes also resulted in a number of observations in the sample not matching into the matrix, given the utilization of "all other" occupational categories in the sample. For instance, a worker's pre- or post-displacement occupation may have been categorized by the DWS as "Engineers, all other." However, the SOC/O*NET system does not have comparable "all other" categories that yield a suitable match; as such, a small percentage of the sample do not find an appropriate home in the transferability matrix given the incongruent nature of their DWS/Census occupation when compared to possible SOC/O*NET vocational codes.

exhibited by those from blue-collar manufacturing jobs. Strikingly, blue-collar workers displaced from nonmanufacturing industries display transfer rates of 78 percent-nearly 10 percentage points higher than those displaced from manufacturing-further cementing the recognition regarding the relative obsolescence of such positions in the labor market.

Turning to "qualification" rates in Table 13, those displaced from blue-collar occupations within the manufacturing industry exhibit lower qualification rates (71.19 percent) in their post-displacement profession compared to their displaced brethren (76.78 percent). This trend generally holds when examining different sectors of the labor market as well, except for the marginally lower rate of clericals (70.93 percent). Nevertheless, conflicting reasons may be responsible for higher qualification rates: a person will exhibit higher rates for finding work in a comparable (or the same) occupation as well as in one in which they are overqualified. In other words, if a plant foreman has to take a job as a manual laborer, he or she will display a high degree of "qualification." However, this would likely represent a negative post-displacement outcome, and the resulting loss of human capital upon this "downward" movement would be captured only through the use of transferability rates.

Limiting the focus to transferability rates, given its importance in establishing labor market effects of economic restructuring, Table 14 displays the estimation of a regression model using transferability rates as the dependent variable. The results indicate that, even after factoring out heterogeneity (e.g., education, age) between occupational groups, individuals displaced from blue-collar manufacturing jobs experience a greater loss of occupation-specific human capital than do their displaced counterparts. Beyond the role of occupational groupings, Table 14 reveals a number of other interesting trends. First, transferability is lower for younger workers, as they may not have had the necessary experience to develop their human capital both across the labor market and within a given occupation. While the effect of a college education has a predictably positive effect on one's ability to find a high-transferable occupation following displacement, it should also be noted that displaced union members tend to exhibit higher transferability rates, *ceteris paribus*, that may speak to differences in *individual* skill levels. Further, those who exhaust their unemployment insurance (UI) benefits tend to experience significantly lower rates of transferability, potentially due to the failure to find a comparable job during the UI period and the subsequent scramble to find *any* job following the exhaustion of benefits.[48]

To establish transferability as a key determinant of post-displacement outcomes, Table 15 provides the results of a regression equation analyzing the effect of transferability rates on weekly earnings of those re-employed for at least twenty hours per week. Controlling for a multitude of variables, the use of ordinary least squares (OLS) in the first model demonstrates a positive effect of transferability on earnings, with the effect significant in greater than a two-sided, one-percent significance test. The coefficient suggests that as the transfer rate goes up by 10 percentage points, earnings will be expected to increase by 6 percent.

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48 A specification of the regression equation separating all occupations into manufacturing and nonmanufacturing groups found comparable results.

TABLE 14. Regression Analysis on Transferability of KSAs from Displaced to Re-Employment Occupation, 2004 DWS

	γ_{ij}: *Transfer*	
	Model 1	*Model 2*
Displaced Occupation		
Professional/Technical Occupations		-0.032* (0.017)
Service Occupations		Base
Sales Occupations		-0.013 (0.019)
Clerical Occupations		0.008 (0.017)
Blue-Collar Occupations, Manufacturing		-0.065*** (0.019)
Blue-Collar Occupations, Non-Manufacturing		0.029* (0.017)
Age		
20-24	-0.046*** (0.017)	-0.048*** (0.017)
25-34	-0.013 (0.011)	-0.015 (0.011)
35-44	Base	Base
45-54	-0.022* (0.012)	-0.023* (0.012)
55-64	0.015 (0.016)	0.012 (0.016)
65 and up	0.032 (0.043)	0.035 (0.042)
Education		
No High School Diploma	0.023 (0.016)	0.022 (0.016)
High School Diploma, No College	Base	Base
Some College, No Degree	0.015 (0.012)	0.014 (0.012)
Vocational or Associate's Degree	0.005 (0.015)	0.008 (0.015)
Bachelor's Degree or More	0.045*** (0.011)	0.059*** (0.013)
Demographics		
Male	0.0001 (0.009)	-0.004 (0.009)
Black	-0.013 (0.016)	-0.011 (0.016)
Other Non-White Race	0.027 (0.018)	0.030* (0.018)
U.S. Citizen	-0.044** (0.018)	-0.043** (0.017)
Married	-0.003 (0.010)	-0.003 (0.010)

TABLE 14. Regression Analysis on Transferability of KSAs from Displaced to Re-Employment Occupation, 2004 DWS (cont.)

Number of Children (< age 18)	-0.003 (0.004)	-0.003 (0.004)
Region		
Northeast	0.042*** (0.012)	0.045*** (0.012)
Midwest	0.005 (0.012)	0.010 (0.012)
South	0.029** (0.012)	0.032*** (0.012)
West	Base	Base
City Status		
In City	0.011 (0.013)	0.010 (0.013)
Balance of City	0.015 (0.012)	0.015 (0.012)
Other City Status	-0.012 (0.014)	-0.013 (0.014)
Non-Metro	Base	Base
Job Characteristics		
Union Member at Old Job	0.066*** (0.015)	0.068*** (0.016)
Tenure at Old Job	-0.002** (0.001)	-0.001* (0.001)
Received Notice of Layoff	0.008 (0.009)	0.012 (0.009)
Exhausted UI Benefits	-0.080*** (0.011)	-0.074*** (0.011)
Constant	0.770 (0.025)	0.772 (0.027)
Observations	2,698	2,698
R-Squared	0.0497	0.0660
F-Statistic on Overall Model	5.58 (p<0.0001)	6.28 (p<0.0001)
F-Statistic on Occupational Variables		9.34 (p<0.0001)

*Notes: Standard errors in parentheses. Significance levels noted as follows: *** - 1 percent, ** - 5 percent, * - 10 percent.*

TABLE 15. Regression Analysis on ln(Weekly Earnings), Among Those Re-Employed and Working at Least 20 Hours/Week, 2004 DWS

	ln(weekly earnings)	
	OLS	*2SLS*
Transfer Rate of KSA*100	0.006*** (0.0008)	0.048* (0.027)
Observations	2,405	2,405
R-squared	0.1507	*
F(31, 2373)	13.59 (p<0.0001)	5.64 (p<0.0001)

*Notes: Other variables include: Male, age (6 categories), education (5), race (3), citizen, union member at lost job, marital status, tenure at lost job, number of children under eighteen, region (4), city status (4), received notice of layoff, exhausted UI benefits, origin occupation (6). Second-stage equation identified by the state's WIA spending per displaced worker in 2001 and an indicator denoting whether the individual lost his or her job via plant closure versus other reasons (slack work, shift abolished). Standard errors in parentheses. Significance levels noted as follows: *** - 1 percent, ** - 5 percent, * - 10 percent.*

The results of the OLS model are biased, however, by the inherent simultaneity between transferability of OSHC and post-displacement earnings. To resolve this, a two-stage least squares (2SLS) approach is utilized. In the first stage, transferability is predicted by the basic set of explanatory variables used previously along with two others: (a) the amount of state spending per displaced worker through the Workforce Investment Act during the year 2001 as the IV, and (b) an indicator variable denoting whether the individual lost his or her job because of a plant closing as opposed to some other reason (e.g., shift abolished).[49] While the use of instrumental variables calls into question the magnitude of the effect of transferability on earnings, the results nevertheless confirm the

49 State-level spending through the WIA is used by local agencies to match the characteristics of displaced workers with the needs of the local labor market, with emphasis on "a quick return to employment"-and not necessarily higher post-displacement wages. Further, the reason behind an individual's displacement speaks to the availability of different types of jobs within the local labor market, as plant closings may indicate a more downtrodden environment for an occupation or industry. Data drawn from the Government Accounting Office report, GAO-02-274: "Workforce Investment Act: Better Guidance and Revised Funding Formula Would Enhance Dislocated Worker Program," February 2002, http://www.gao.gov/new.items/d02274.pdf.

previous findings that higher transferability of OSHC upon re-employment has a positive, statistically significant effect on post-displacement earnings.

DISCUSSION

While the manufacturing sector is at its lowest level of employment since 1950, evidence of structural unemployment affecting blue-collar, manufacturing workers has been largely circumstantial. As a part of a broader analysis of post-displacement occupational outcomes within this group, this paper provides evidence that directly confirms the "structural victim" status of those displaced from blue-collar, manufacturing jobs. Significantly lower rates of both re-employment and transferability of occupation-specific human capital afflict those displaced from this sector. However, the occupational analyses presented here demonstrate that typecasting laid-off workers from this sector as future low-level service or sales associates is largely unrealistic. In contrast, twenty years of data reveals marginally rising absorption rates of displaced blue-collar manufacturing workers by professional specialty and administrative support occupation groups while absorption rates by sales and service occupations have remained flat. Further, given the importance of the transferability of OSHC in establishing post-displacement earnings, future research should go beyond its typical focus on wages to examine why certain groups fare better upon re-employment and how public policy can best aid those who are the casualties of structural shifts in the economy.

Beyond these results, the greater long-term contribution of this paper may be the development of a 900 x 900 occupation transferability matrix of KSAs based on occupational descriptions provided by O*NET. This matrix represents a significant improvement from Shaw's (1984) original attempt to estimate cross-occupation transferability of human capital using occupational switching proxies. With a growing literature awakening to the impact of occupation-specific human capital, the development of this matrix may serve as a valuable statistical lens through which to examine a wide range of labor market questions, including the identification of comparable-and expanding-occupations for displaced workers that may lead to greater percentages of retraining success.

Chapter 3

HIGH SCHOOL EMPLOYMENT AND THE ACCUMULATION OF OCCUPATION-SPECIFIC HUMAN CAPITAL

INTRODUCTION

While labor market participation rates among high school students in the United States dominates that of most other industrialized countries (Alsaker and Flammer 1999; Fuligni and Stevenson 1995), research efforts have yet to completely untangle the positives and negatives associated with in-school employment amongst secondary school students. On one hand, working during high school is posited to negatively affect academic performance and attainment, a stance generally borne out in the literature (Marsh and Kleitman 2005; Rothstein 2007). On the other hand, nearly three decades of research have consistently demonstrated that high school employment has a positive effect on post-school economic outcomes such as earnings, employment, and occupational attainment.

Despite the pervasiveness of the research demonstrating a positive relationship between in-school work and future economic gains, the literature is silent in regards to why this association exists. While studies establishing this positive relationship hypothesize that it is attributable to the role of high school employment as a positive net influence on human capital (DeSimone 2006; Light 1999; Ruhm 1997), such a statement is made without empirical evidence and lacks specificity given the complex nature of human capital (as discussed in Chapter 1). In particular, does high school employment develop "marketable skills" within the student that represent specific human capital? Or could it be that in-school employment builds character and socializes one to the workplace, thus providing general human capital? Or could it be that the positive association between high school employment and future economic outcomes is not attributable to human capital differences at all?

Given the empirical silence regarding these questions, this paper makes the first known foray to investigate the potential rationale behind the positive relationship between high school employment and post-school economic outcomes. To such ends, this paper addresses the first possibility above, namely that in-school employment instills marketable skills–defined in this paper to be occupation-specific human capital (OSHC)–that represent the causal influence explaining why high school employment is suggested to yield post-school economic gains. By the tenets of the human capital model, it is expected that greater applicability of one's learned occupational skills from high school employment to one's adult (post-school) vocation should result in higher productivity, and thus higher wages. To test this hypothesis, this study utilizes eight rounds of data from the 1997 National Longitudinal Survey of Youth (NLSY97) and multiple measures of OSHC transferability, including the OSHC matrix provided in Chapter 2. If it is confirmed that higher transferability of skills from one's senior-year vocation to one's adult profession yields positive wage effects, then this would stand as at least part of the reason for the consistent finding of a positive relationship between in-school work and post-school economic outcomes.

LITERATURE REVIEW

The research agenda on high school employment has historically had a heavy focus on the potentially deleterious effect of in-school work on academic performance, as measured by grades, test scores, or school completion rates. No consensus currently exists about whether student employment improves or impairs high school academic performance, however the evidence seems to suggest that any effects—positive or negative—are minimal at low and intermediate levels of work intensity. Meanwhile, there is overwhelming evidence that heavy work commitments have strong negative effects on academic outcomes. While this has generally been viewed as a threshold effect (D'Amico 1984; DeSimone 2006; McNeal 1995, 1997; Schill, McCartin, and Meyer 1985), others have suggested that the negative effect of work hours on academic performance is linear (Marsh and Kleitman 2005).

Contrary to the above, research has consistently demonstrated that high school employment has a positive association with future economic outcomes. D'Amico (1984) and Marsh (1991) demonstrated that holding a job while in high school was associated with lower post-school unemployment rates. Stephenson (1981), Meyer and Wise (1982), and Mortimer and Finch (1986) showed that in-school employment was related to higher future incomes. Mortimer and Finch (1986) illustrated that high school job holding was correlated with higher post-school occupational attainment. Despite their consistent conclusions, these studies suffered from two primary flaws: each only examined the immediate period following school completion and they treated in-school employment as exogenous; by doing so, the studies ignored the selection process of individuals into the workforce.

In an attempt to rectify both issues, Ruhm (1997) utilized data from the NLSY79 to demonstrate that hours worked during one's senior year was positively correlated with higher earnings, fringe benefits and occupational status six to nine years following school completion. A breakthrough work for its application of sample-selection corrections as a means of identifying and resolving the inherent endogeneity issues, Ruhm estimated that working twenty hours per week as a senior is associated with a 9 percent boost in hourly wages and an 11 percent increase in hourly compensation as an adult. Light (1999) addressed the underlying question of whether job-holding in high school served as a "value added" experience, or whether high school employment raised future labor market productivity beyond any losses attributable to lowered academic performance. Light analyzed a set of male terminal high school graduates to examine the influence of high school employment, high school curriculum, and future work experience on earnings for the first nine years following school completion. Finding small, but significant, positive gains to high school work intensity on future earnings, Light concluded "high school employment has a positive, skill-enhancing effect on wages for the first six years after graduation," (p. 305).

Light's conclusion, similarly suggested by Ruhm (1997) and DeSimone (2006), speaks to the common belief regarding the source of the positive relationship between high school employment and future economic outcomes: in-school work generates a net increase in human capital. If this is indeed true, such a statement linking in-school work and human capital development lacks specificity. In particular, while the phrase "human capital" is typically used as a catch-all for skill and knowledge development, the construct itself is quite complex (as discussed in Chapter 1). As a result, understanding how high school employment affects human capital stocks is critical to explain why in-school work results in future positive economic outcomes. Is the positive earnings impact of in-school work attributable to increases in occupation-specific human capital under the rubric of "marketable skills"? Or could it be that the positive relationship is due to increases in general human capital, such as building character and socialization to the workplace? These questions are vital to understand the impact of high school employment on future economic outcomes.

This paper examines this first question, namely whether high school employment develops occupation-specific human capital that may be the underlying causal factor relating in-school work and adult economic gains. Shaw (1984) defined occupation-specific human capital as "the accumulation of skills an individual acquires to perform work within an 'occupation'" (p. 320).[50] Distinguishing occupation-specific from firm-specific human capital, Shaw noted that not all of one's occupation-specific human

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50 Shaw (1984) defines an "occupation" as "a homogeneous skill classification within which individuals are perfect substitutes in demand and/or have infinite cross elasticities of substitution in supply. Cabinet-makers and engineers, for example, have occupation-specific skills," (p. 320).

capital is lost upon a vocational switch. Instead, individuals are able to "transfer" certain proportions of their accrued OSHC from one vocation to another based on the commonality of skill sets required for the two occupations. For example, an accountant would be able to transfer a large percentage of their accrued OSHC into their new role as an actuary; in contrast, an accountant would experience low transferability rates if they became an electrician. The foundational work of a small but growing literature on occupation-specific human capital, Shaw demonstrated that accrued occupation-specific human capital dominated general experience in determining wages; later studies showed OSHC to also dominate industry- and firm-specific human capital in terms of predicting earnings (Kambourov and Manovskii 2004, 2005). Given the significant influence of accrued occupation-specific human capital on earnings, the development of OSHC through high school employment could serve as a sizeable factor linking in-school work and adult economic gains. While Stern and Nakata (1989) demonstrated that different in-school jobs utilize varying types of skills, one would nonetheless expect that those who were able to transfer more of their learned skills from their high school vocation to that of their adult profession would be more productive, and thus earn more, all else equal.

DATA AND MODEL

To address the question of whether the positive relationship between high school employment and higher future earnings is attributable to the accumulation of occupation-specific human capital, this paper utilizes data from the 1997 National Longitudinal Survey of Youth. This data set tracks 8,984 individuals who were aged 12-16 in 1997, following up with yearly questionnaires surrounding each respondent's income, labor market status, educational attainment, and a variety of other characteristics. The successor to the still-active NLSY79, eight rounds of data from the NLSY97 were publicly available at the time of this paper, spanning 1997-2004. While having only eight years of data limits the time horizon to study adult outcomes compared to research featuring the NLSY79, this is counterbalanced by the fact that (a) many prior studies have used short time horizons to study post-schooling outcomes, and (b) the NLSY97 provides significantly more timely data than the NLSY79.

In order to compute the effect of accrued occupation-specific human capital on adult outcomes, it is necessary to first obtain information about a person's occupation while in high school and their vocation as an adult, and then demonstrate how the transferability of OSHC between professions relates to their post-schooling level of earnings. In other words, the basic earnings model (below) applies, with "OSHC" representing an estimate of the transferability of accrued human capital from one's high school vocation into one's occupation two years following school completion. The "firm" variable denotes employment with the same company at both time periods and is included in order to tease out potential tenure, or firm-specific, effects (Note that X_i represents a standard vector of social and demographic variables):[51]

$$\ln(\text{wage}_i) = \beta_0 + \beta_1 X_i + \beta_2 \text{OSHC}_i + \beta_3 \text{firm}_i + \varepsilon_i$$

51 Wage is the CPI-inflated wage for the year representing the second following high school completion.

With a positive coefficient on OSHC confirming the development of marketable skills through in-school work, the composition of this variable requires some explanation. First, it is necessary that an individual divulge an occupation for the two time periods utilized in this study: four months prior to, and two years following, high school completion. Considering that most policy and research analyses of in-school employment focus on the effects of non-seasonal work, the use of the former date captures an individual's senior-year occupation in February of most traditional academic calendars. Further, the use of senior-year employment follows from Ruhm (1997), who demonstrated its dominance compared to sophomore-year and junior-year job-holding in predicting future earnings.

This paper employs three measures of the transferability levels of occupation-specific human capital from their in-school to post-school occupations. The first method groups each vocation into one of 14 categories aligned with the 2002 Standard Occupational Classification (SOC) system.[52] Thus, to gauge whether an individual can apply occupation-specific human capital from their high school vocation to their adult occupation, this method of calculating OSHC is an indicator variable equaling one if both the adolescent and adult occupations fall into the same category. For example, this indicator would equal one if an adult sales manager had worked as a retail sales clerk in high school; it would similarly equal zero if that sales manager had been employed as a carpenter's assistant.

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52 Most occupational categories are based upon the first two digits of the relevant SOC codes. However, given the lack of observations in the "white-collar" occupational categories, these have all been collapsed into a singular "management and professional" classification for use in this study.

While the above method is empirically simple, it is not altogether an accurate representation of the transferability of occupation-specific human capital from one's high school vocation to their adult occupation. For example, due to the structure of the SOC, the above method would affix a value of zero to the transferability of OSHC between retail sales clerks and, say, marketing managers despite the fact that acquired skills of persuasion and customer service would be a benefit across professions—and thus non-zero. Therefore, to gauge more accurate predictions of cross-occupation transferability of OSHC, this study turns to the transferability matrix advanced in Chapter 2. This matrix estimates the transferability of occupation-specific human capital from occupation i to occupation j using data from O*NET, the U.S. Department of Labor's database that provides rankings of 900 distinct occupations across 120 knowledge, skill, and ability categories. Applied to the 508 detailed occupational codes employed by the NLSY97,[53] the matrix provides two measures that will be utilized in this work: (a) t_{sa}, the proportion of OSHC transferred from one's student vocation to their adult occupation, and (b) q_{sa}, the proportion to which the acquired OSHC in one's student vocation makes an individual qualified to work in the adult profession. As described more thoroughly in Ormiston (2006), these proportions are estimated by calculating the ratio of the shared

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53 In regards to the incongruence between the 900 O*NET occupations the 508 utilized by the NSLY97, occupations are mapped one-to-one when available. Where more than one O*NET occupation is assigned to a relevant NSLY97 occupation, mean values of the O*NET scores are used. While imperfect, this represents the best available means of matching occupations, as demonstrated by Hirsch (2005) and Ormiston (2006).

knowledge, skill, and abilities used within both the student and adult vocations to the total amount of KSAs utilized within one of the occupations alone.[54]

To understand these definitions, consider the case of a high school student who works as a retail salesperson while enrolled, and later becomes a sales engineer. As constructed, the transferability matrix suggests that 96.17 percent of the knowledge, skills, and abilities utilized on the job as a retail salesperson could be applied to one's role as a sales engineer (i.e., $t_{sa} = 0.9617$). On the flip side, the matrix indicates that employment as a retail salesperson would utilize only 41.45 percent of the knowledge, skills, and abilities necessary to function as a sales engineer (i.e., $q_{sa} = 0.4145$). While the former has particular relevance to earnings (Shaw, 1984), the latter is of particular importance in predicting occupational entry. For robustness, both measures are included in the analysis.

The sample of interest from the NLSY97 is restricted in three ways. First, respondents must have been employed—and thus had an occupation—four months prior, and two years following, their high school graduation. This is central to examining occupational comparability across time periods.[55] Second, the sample is restricted to include only males given that there are gender differences in both high school employment (Michael and Tuma, 1984; Ruhm, 1997) and post-school job-holding characteristics (Oaxaca,

54 The denominator of t_{sa} is the student occupation, while the denominator of q_{sa} is the adult occupation.

55 By limiting the sample to those who worked while in high school, this inherently eliminates the endogeneity central to the works of Ruhm (1997) and Light (1999), and which plagued prior studies linking high school employment to future economic outcomes. In other words, there are no concerns in this work about the selection process of high school students into employment since all observations will have made that selection.

1973; Macpherson and Hirsch, 1995). The final restriction follows the lead of Light (1999), as the sample is limited to only terminal high school graduates with no college experience.[56] This is done for two reasons. First, the restricted focus on this sub-sample eliminates much of the underlying, unobserved heterogeneity (e.g., motivation, ability) that is involved in occupational attainment and earnings, as well as eliminates the conflating influence of college enrollment on job outcomes. Second, if high school employment does significantly build occupation-specific human capital responsible for the positive relationship between in-school work and adult earnings, this outcome should be most prevalent amongst non-college graduates given the differences in post-schooling occupational outcomes across educational groups. For example, working as a retail salesperson while in high school would likely have considerably more influence on the occupational and wage outcomes for terminal high school graduates than for college graduates given differences in the types of occupations available to each in the labor market.

Table 16 provides summary statistics on the sample of 356 that were employed at both points in the study and had an adult hourly wage between \$2.00 and \$50.00 (to eliminate non-respondents and outliers).[57] As might be expected, high school employment is clustered into a limited number of occupational categories, especially food preparation and serving, sales and related, and transportation and material moving vocations. The distribution of adult vocations differs slightly, with the most notable difference coming in

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56 This also excludes those who acquire a GED degree.

57 Note that while 356 is not an overly large sample, the availability of future rounds of data should expand this sample considerably. It should be noted that Light (1999) worked with a sample of 685 individuals from the NLSY79.

the decrease in percentage of respondents employed in food preparation and serving occupations (25.84 to 12.08 percent) compared with in-school employment. The overall mean real hourly wage for terminal high school graduates two years following graduation was \$10.21. What is most interesting from Table 16 is that 37.9 percent of individuals maintained a post-school occupation in the same category as the job they held four months prior to school completion. Further, 20.2 percent of the sample was employed by the same company for which they worked as a high school senior. Whether this is the result of a cognizant effort by terminal high school students to find the appropriate career before graduation, or merely the post-school continuation of high school employment, remains to be seen however represents a key issue to be examined in future research.

Table 17 summarizes the mean real hourly wage according to occupation and employer status. The results demonstrate that there is no statistically significant difference in mean wages across any employment characteristics. For instance, those whose in-school and post-school jobs fall in the same occupational category earn, on average, \$10.26 per hour while those with different occupations across the two time periods earn \$10.19, a difference that fails to be significant ($t = 0.02$, $p = 0.8952$). Further, regardless of occupation, those employed by the same firm at both periods earn, on average, \$10.41; by comparison, those who change employers earn, on average, \$10.16. This difference also fails all reasonable thresholds of statistical significance ($t = 0.15$, $p = 0.7006$). An F-test also fails to uncover any statistically significant differences in the mean wages of the four combinations of occupation and firm status ($F = 0.08$, $p = 0.9717$). While the results of Table 17 are hindered by sample size limitations, it nevertheless fails to demonstrate any

TABLE 16. Summary Statistics

Variable	*Mean / Percent*	
Real Hourly Wage, Two Years Following HS	\$10.21	
Race/Ethnicity		
White / Other	0.612	
Black	0.171	
Hispanic	0.216	
Region (during HS)		
Northeast	0.197	
North Central	0.281	
South	0.334	
West	0.185	
MSA Status (during HS)		
City	0.247	
Suburbs	0.497	
Other	0.256	
Other Social Variables		
Married, Two Years Following HS	0.084	
Union Member, Two Years Following HS	0.087	
ASVAB Score (percentile)	29.72	
Smoked Marijuana in High School	0.449	
Second Language Spoken at Home	0.163	
Occupation	*HS: Senior Year*	*Adult*
Management and Professional	0.0197	0.0562
Entertainment and Media	0.0084	0.0112
Health Care and Support	0.0084	0.0169
Protective Service	0.0056	0.0337
Food Preparation and Serving	0.2584	0.1208
Cleaning and Building Service	0.0506	0.0478
Service, including Attendants and Personal Care	0.0365	0.0169
Sales and Related	0.1629	0.1124
Office and Administrative Support	0.0758	0.0927
Farming, Fishing, and Forestry	0.0253	0.0140
Construction and Extraction	0.0815	0.1348
Installation, Maintenance, and Repair	0.0618	0.0983
Production, including Operators and Tenders	0.0337	0.0815
Transportation and Material Moving	0.1713	0.1629
OSHC		
Same Occupational Category, Adult and High School	0.379	
q_{sa}	0.681	
t_{sa}	0.735	
Same Employer, Adult and High School	0.202	
Observations	356	

TABLE 17. Mean Hourly Wage by Occupational and Employer Status

	Observations	*Mean Hourly Wage*
Overall Sample	356	\$10.21
Same Occupation While in High School	135	\$10.26
Different Occupation While in High School	221	\$10.19
t-test for Differences in Means		t = 0.02
Same Employer While in High School	72	\$10.41
Different Employer While in High School	284	\$10.16
t-test for Differences in Means		t = 0.15
Same Occupation, Same Employer While in HS	70	\$10.43
Same Occupation, Different Employer While in HS	65	\$10.07
Different Occupation, Same Employer While in HS	2	\$9.63
Different Occupation, Different Employer While in HS	219	\$10.19
F-test for Differences in Means		F = 0.08

Note: "Occupation" is defined as the 14 categories listed in Table 1.

prima facie evidence of the influence occupation-specific or firm-specific human capital in dictating post-schooling wages.

RESULTS

While the summary approach taken in Table 17 failed to validate the influence of occupation-specific or firm-specific human capital in predicting post-school wages, a more careful analysis of the matter is undertaken through the estimation of the wage equation presented earlier in this paper. Table 18 presents the results of a wage equation that first excludes the "firm" variable indicating employment with the same company at both the in-school and post-school time periods. Contrary to the summary results of Table

TABLE 18. Regression Analysis on ln(Hourly Wage), Without Firm Controls

Ln(wage)	*Same Occupational Category*	t_{sa}	q_{sa}
Race/Ethnicity			
Black	-0.028 (0.060)	-0.023 (0.060)	-0.036 (0.060)
Hispanic	-0.026 (0.070)	-0.025 (0.071)	-0.027 (0.070)
White / Other	Base	Base	Base
Region			
Northeast	0.094* (0.055)	0.093* (0.055)	0.089 (0.056)
North Central	0.053 (0.051)	0.048 (0.051)	0.046 (0.051)
South	Base	Base	Base
West	0.080 (0.062)	0.073 (0.062)	0.073 (0.062)
MSA Status			
City	-0.037 (0.049)	-0.041 (0.049)	-0.034 (0.049)
Suburbs	Base	Base	Base
Other	-0.100** (0.047)	-0.103** (0.047)	-0.097** (0.047)
Married at 20	0.065 (0.070)	0.065 (0.070)	0.068 (0.071)
Union Member at 20	0.155** (0.070)	0.156** (0.070)	0.151** (0.070)
ASVAB pct * 100	-0.0005 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Smoked Marijuana in HS	-0.034 (0.040)	-0.030 (0.040)	-0.033 (0.040)
Second Language at Home	0.012 (0.077)	0.011 (0.077)	0.014 (0.077)
OSHC	0.078* (0.041)	0.170* (0.100)	0.132 (0.086)
Occupation at age 20 (14 categories)	Yes	Yes	Yes
R-squared	0.2669	0.2652	0.2640
Observations	356	356	356

*Notes: Standard errors in parentheses. * - p<0.10; ** - p<0.05; *** - p<0.01.*

17, the regression estimates in the first column of Table 18 demonstrate that, among terminal high school graduates, those who stay within the same occupational category earn 7.8 percent more than those who have switched occupations, ceteris paribus, a result significant in a one-tailed, 5-percent test. Buttressed by reasonable coefficients on the other variables in the model, the positive coefficient on OSHC is suggestive of a significant influence of high school employment in the generation of "marketable skills," considered by this study to be the development of occupation-specific human capital, on post-school wages.

The finding that high school employment develops occupation-specific human capital is further supported by the coefficient on OSHC transferability in the second and third columns of Table 18. The results using t_{sa} suggest that a 10-percentage point increase in the transferability of occupation-specific human capital from one's high school vocation to their adult profession would be expected to increase wages by 1.70 percent. The coefficient on t_{sa} is significant in a one-tailed, 5-percent test, and the remaining coefficients are of reasonable sign and magnitude. The results in the third column of Table 18 also support the hypothesis that in-school employment augments occupation-specific human capital, as the coefficient on q_{sa} indicates that a 10-percentage point increase in the proportion to which in-school employment makes one qualified for the post-school occupation would be expected to increase wages by 1.32 percent. This effect is statistically significant in a one-tailed, 10-percent test.

While the results of Table 18 are indicative of significant positive effects of occupation-specific human capital acquired through high-school employment on post-school economic outcomes, these results disappear upon introducing a control variable indicating whether the individual works for the same employer that they did while in high school. The results of Table 19 demonstrate that upon accounting for firm-specific human capital, as denoted by employment with the same firm both while enrolled and two years following graduation, the coefficients on all three OSHC variables are no longer significant at any reasonable statistical threshold. For instance, the coefficient on OSHC in the first column suggests that post-school employment in the same vocational category that one was working as a high school senior would be associated with a 6 percent wage premium. However, such a result fails to be statistically significant ($t = 1.17$, $p = 0.241$). This trend of positive, yet not statistically significant, coefficients on OSHC is mirrored in the second and third columns of Table 19, as noted by the coefficients on t_{sa} ($\beta = 0.114$, $t = 0.88$, $p = 0.379$) and q_{sa} ($\beta = 0.070$, $t = 0.59$, $p = 0.554$). All other coefficients within these models are of reasonable sign and magnitude.

There are two possible explanations for the failure of the OSHC coefficients to remain statistically significant upon the inclusion of the firm variable. First, the results of Table 18 may be the product of omitted variable bias, as the predicted OSHC effect might be capturing both occupation-specific and firm-specific influences. Exacerbated by the disproportionate number of individuals working in the same occupation that are also employed by the same firm, one would expect that excluding employer controls would

TABLE 19. Regression Analysis on ln(Hourly Wage), With Firm Controls

Ln(wage)	*Same Occupational Category*	t_{sa}	q_{sa}
Race/Ethnicity			
Black	-0.026 (0.060)	-0.022 (0.060)	-0.029 (0.060)
Hispanic	-0.025 (0.070)	-0.023 (0.071)	-0.024 (0.071)
White / Other	Base	Base	Base
Region			
Northeast	0.094* (0.055)	0.093* (0.056)	0.090 (0.056)
North Central	0.052 (0.051)	0.047 (0.051)	0.046 (0.051)
South	Base	Base	Base
West	0.077 (0.062)	0.072 (0.063)	0.071 (0.062)
MSA Status			
City	-0.039 (0.050)	-0.043 (0.050)	-0.039 (0.050)
Suburbs	Base	Base	Base
Other	-0.104** (0.048)	-0.107** (0.048)	-0.104** (0.048)
Married at 20	0.067 (0.071)	0.068 (0.071)	0.070 (0.071)
Union Member at 20	0.156** (0.070)	0.156** (0.070)	0.153** (0.070)
ASVAB pct * 100	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Smoked Marijuana in HS	-0.033 (0.040)	-0.029 (0.040)	-0.031 (0.040)
Second Language at Home	0.012 (0.077)	0.012 (0.077)	0.013 (0.077)
OSHC	0.061 (0.052)	0.114 (0.129)	0.070 (0.118)
Worked at Same Firm	0.033 (0.061)	0.042 (0.063)	0.051 (0.066)
Occupation at age 20 (14 categories)	Yes	Yes	Yes
R-squared	0.2676	0.2663	0.2653
Observations	356	356	356
F(2,328) on OSHC and Firm Variables	1.68	1.46	1.98

*Notes: Standard errors in parentheses. * - p<0.10; ** - p<0.05; *** - p<0.01.*

lead to an upward-biased coefficient on OSHC. That said, an alternative explanation of the decreased significance of the OSHC coefficients in Table 19 would be suggestive of collinearity between occupation and firm controls, and there is some evidence from the data supporting this hypothesis.[58] Therefore, especially considering the sample size limitations of this paper, the conclusions drawn from the results of Table 19 must be tempered by the recognition of potential collinearity effects in the absence of more sophisticated controls.[59]

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58 Potential evidence of collinearity between the OSHC and firm variables is three-fold. First, the coefficients on the OSHC and firm variables are significant when the other variable is excluded from the model, but fail to be significant upon the inclusion of the other as indicated in Table 19, including a lack of joint significance as denoted by the F-statistic. Second, there is considerable correlation between the three OSHC variables and the employer control (e.g., $r = 0.6424$ for t_{sa} and the firm indicator). Finally, the computed VIFs for the occupation and firm variables from the models specified in Table 19 range from 1.74 to 2.15.

59 An alternative specification of the results would be to include individuals who did *not* work four months prior to high school graduation and setting all three of their OSHC variables equal to zero since there would be no transferability of occupation-specific human capital from in-school employment to post-school work. A concern with this specification would be that, absent other controls, occupation and firm variables would be proxying for the labor supply decision made in high school that was found to be significant in Ruhm (1997) and Light (1999), among others. In other words, the move from t_{sa}=0.30 to t_{sa}=0.40 is drastically different than the move from t_{sa}=0 to t_{sa}=0.10; while the former speaks of differences in the OSHC transferability of in-school employment, the latter represents the move from the non-employment to employment while enrolled in secondary school. As a means of correcting this, the specification applied here includes an indicator variable denoting whether a person worked in high school. The results of this strategy are included in Appendix C. While this model may suffer from even more substantial collinearity than the specification of Table 19, the results of this specification suggest a similar outcome: small, positive coefficients on the occupation-specific and firm-specific human capital variables, each of which fail to be statistically significant in any reasonable test. Another potential concern about the results of Table 19 are that they might be influenced by selectivity bias considering the restrictions of the sample to only include terminal high school graduates. In other words, this analysis could be clouded by endogeneity given the potential influence of in-school employment in dictating educational choice, particularly the decision to pursue higher education. However, the application of a multinomial logit sample selection correction outlined in Bourguignon, Fournier, and Gurgand (2007)—across a variety of academic outcome structures—yielded no significant evidence of endogeneity. Full results are available from the author.

DISCUSSION

Recent, more sophisticated efforts by Ruhm (1997) and Light (1999) have only confirmed what decades of prior research illuminated: high school employment is positively correlated with post-school economic outcomes, including earnings. To this point, the standard causal inference has been that working while attending secondary school allows an individual to accrue "marketable skills" that they can apply in the labor market, an increase in human capital stock that generates higher wages. This paper has examined this hypothesis using data from the NLSY97 on terminal high school graduates, defining the generation of marketable skills as the development of occupation-specific human capital. To confirm the role of high school employment as a significant "skill-enhancing" influence, one should find higher rates of OSHC transferability between high school and adult vocations associated with higher earnings.

On the surface, the results of this paper cast some doubt on the hypothesis that high school employment provides a means of generating marketable skills. While simple models exhibited positive, significant effects of occupation-specific human capital transferability, these influences disappeared once firm-specific effects were introduced. However, potential collinearity between variables—exacerbated by a limited sample size[60]—suggests that this paper by no means represents the final word on the prospect of high school employment generating marketable skills that are responsible for the post-

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60 As future rounds of the NLSY97 become available, this paper will be updated to reflect the increase in available observations, as well as explore the influence of occupation-specific human capital on a longer time horizon of post-school economic outcomes given its potential obsolescence over time (Ruhm, 1997).

schooling economic gains of in-school job holding. A more careful analysis, including a larger sample size, longer time horizon, and more sophisticated measures, may be necessary to provide a more definitive conclusion regarding the hypothesis that employment during secondary school instills marketable skills utilized in the labor market during adulthood.

Regardless of the above results, it is hoped that the questions posed in this paper may lead to a more careful analysis of the causal factors behind the positive relationship between high school employment and post-school economic outcomes. In particular, efforts to link in-school work with post-school gains routinely cite increases in human capital, however such statements lack specificity and empirical backing. Thus, it is an open question to determine how high school employment affects an individual's complex human capital stock as well as identifying potential institutional reasons behind the positive relationship between in-school work and post-school outcomes. To the latter point, a full examination of the topic must consider high school employment as a classic "signal" in the labor market; having prior work experience gives otherwise similar individuals a distinct advantage in hiring and wage-determination outcomes. In addition, prior employment may alter job-search strategies. Following exposure to entry-level positions, more experienced workers may be more likely to actively initiate job search strategies to locate higher-paid openings and have the self-efficacy to obtain such a position given their prior work history.

With decades of research demonstrating the positive effect of in-school employment on post-school economic outcomes, it is imperative to begin to untangle the rationale behind such a relationship, as well as how high school employment affects human capital, job search strategies, occupational choice, and hiring and wage decisions on the part of potential employers. Considering the potential negative academic outcomes attributed to in-school employment, it is important to recognize how and why students benefit from holding a job in order to tailor both parental and policy decisions. While this study has provided initial evidence casting some doubt on the relevance of high school jobs in building marketable skills, the issue is far from resolved; there remains significant work to be done to fully understand the dynamics relating in-school employment to both human capital formation and post-school economic outcomes.

APPENDIX A

EXAMINING OCCUPATION AS A MEDIATOR BETWEEN EDUCATION AND WAGES

In examining the possibility that occupation serves as a *mediator* to the effect of education on wages, one can turn to Baron and Kenny (1986) to examine the issue. The authors describe a mediator relationship as follows: "In general, a given variable may be said to function as a mediator to the extent that it accounts for the relation between the predictor and the criterion... Whereas moderator variables specify when certain effects will hold, mediators speak to how or why such effects occur," (p. 1176). Full mediation, in this scenario, would suggest that education operates solely through occupation; in contrast, partial mediation recognizes the possibility of education effects wages two ways – independently and through its role in occupational selection.

Given the above, a model of occupation as a mediator in the wage equation envelops many of the relationships stressed in the better part of this paper. First and foremost, it recognizes that the influence of education on wages can maintain both a direct and indirect effect. As espoused by human capital theorists, this relationship allows for the direct impact of schooling on wages, presumably through the development of one's human capital stock. However, the causal links inherent in the model acknowledge that education also serves as a means of entry into particular occupations, through which vocational-specific wage structures influence the outcome variable. As such, occupation serves as a "how or why" individuals earn specific incomes based on their human capital characteristics, thus mediating the relationship between education and earnings. Therefore, the notion of occupation as a mediator explicitly captures the human capital argument as well as the signaling/occupational contention advanced by Fogel (1979), amongst others.

In turning to Baron and Kenny (1986), demonstrating a mediated relationship in this situation requires three things. First, turning to Figure 2, a regression of education on occupation must yield a statistically significant coefficient on the independent variable. Likewise, a second condition mandates that a regression of occupation on wages results in a statistically significant coefficient on the independent variable. Finally, a regression of education and occupation on wages statistically reduces the coefficient on education when compared to a regression of education on wages. In other words, the three conditions are as follows:

(a) occupation = $\beta_0 + \beta_1$education + ε_i

(b) wages = $\alpha_0 + \alpha_1$occupation + ε_j

(c) wages = $\delta_0 + \delta_1$education + $\delta_2$occupation + ε_k

(d) wages = $\rho_0 + \rho_1$education + ε_m

Condition (1): $|\beta_1| > 0$

Condition (2): $|\alpha_1| > 0$

Condition (3): $|\rho_1| > |\delta_1|$

While the above method of demonstrating mediation may seem straightforward, difficulty arises in the present case since occupation is not a quantitative variable in which one can apply OLS, as occupational choice models typically employ unordered, logit estimation methods (e.g., Schmidt and Strauss 1975). This is problematic in this situation, as Condition (1) becomes nonsensical in the face of such a logit estimation procedure. To rectify this issue, the determination of mediation requires occupation, as the dependent variable in (a), to be a continuous measure aligned with the causality of the model espoused in Figure 2. In particular, the path from education to occupation to wages represents the contentions of Fogel (1979) and that of the signaling literature, namely that schooling serves to unlock doors to "good" jobs that feature elevated wages.

One's first inclination towards a quantitative proxy for occupation may be measures of occupational prestige or socioeconomic indices, as each serves measures the social "goodness" of a vocation. However, how these measures are constructed introduces a reverse causality between wages and occupation, as the occupation variable would be partially determined by the level of wages attributed to it. As such, this introduction of reverse causality would invalidate occupation as a mediator, as defined in Baron and Kenny (1986).

Given the causal conditions required to test mediation, an alternative approach would be to proxy occupation with the amount of knowledge required by the vocation, as it could be argued that one of education's primary goals is to equip students with the knowledge necessary to obtain, and succeed in, a position within a particular vocation. As such, one can exploit the information provided by ONET, a service offered by the US Department of Labor that replaced the Dictionary of Occupational Titles (DOT) as the government's source of information on the knowledge, skills, abilities, and work activities for hundreds occupations across the country. Within the ONET database, each occupation is scored on the importance (rated from 1-5) and level (rated from 0-7) of 33 different knowledge categories. Given that most post-secondary educational programs are designed to impart specific knowledge, this paper captures each occupation's knowledge requirement by multiplying each knowledge importance (IM) score with its corresponding level (LV) score for each vocation while utilizing a linear education variable. As such, "occupation" is thus the calculation of:

$$(1) \quad Occupation_m = \underset{j=m}{Max} \sum_{i=1}^{33} (IM_{ij})(LV_{ij}) \quad ,$$

where j represents each occupation and i denotes each of the 33 knowledge categories. Any incongruities between the PUMS data and the more-specific occupational coding structure of ONET are resolved by averaging separate ONET occupations found underlying SOC codes employed by the PUMS data, a method employed by Hirsch

(2005). By utilizing the maximum knowledge score for each occupation, the vocational score meets the criteria called for – a continuous variable ranging in possibility from 0 to 35 with strong, one-way causal inferences from education to occupation and occupation to wages (and not in the reverse). In addition to its theoretical benefits, the occupational scores also make intuitive sense, with the top scoring occupations listed below:

APPENDIX TABLE A1. Top-Scoring Occupations and Knowledge Categories According to O*NET Rankings

Occupation (SOC Code)	*Score*	*Knowledge Category*
Sociologists (19-3041)	33.45	Sociology
Mathematicians (15-2021)	33.30	Mathematics
Interpreters and Translators (27-3090)	33.30	Foreign Language
Computer Hardware Engineers (17-2061)	33.30	Computers & Electronics
Aerospace Engineers (17-2011)	32.63	Engineering & Technology
Actuaries (15-2011)	32.44	Mathematics
Astronomers and Physicists (19-2010)	32.35	Physics
Physicians and Surgeons (29-1060)	32.19	Medicine and Dentistry
Computer Software Engineers (15-1030)	32.15	Computers & Electronics
Instructional Coordinators (25-9031)	31.70	Education & Training

While not perfect, the results give the highest scores of vocations typically requiring the most schooling regardless of pay levels – physicians and surgeons, astronomers and physicists, mathematicians, etc.

With the variables in hand, the computation of the four equations produces the following estimations (standard errors in parentheses):

(a) occupation =	7.3886 +	0.9541*education (0.0029)		
(b) ln(wage) =	2.0969 +	0.0363*occupation (0.0002)		
(c) ln(wage) =	1.4695 +	0.0691*education (0.0003)	+	0.0210*occupation (0.0002)
(d) ln(wage) =	1.6244 +	0.0891*education (0.003)		

In examining the estimation results above, it is obvious that the first two conditions necessary to confirm occupation's place as a mediator hold, as the coefficients in equations (a) and (b) are indeed statistically significant, indicating a positive impact of education on occupation, and of occupation on wages. For the third condition, the results in equations (c) and (d) indicate a direct effect of 0.0691 of education on the log wage variable, with an indirect effect of 0.0200 (0.0891-0.0691) of education on log wage operating *through* the occupation variable. To verify that occupation serves as a mediator, it must be shown that the indirect effect is statistically significant, thus fulfilling Condition (3). From Baron and Kenny (1986), it can be shown that the standard error of this indirect effect is:

$$s_{indirect} = \sqrt{b^2 s_a^2 + a^2 s_b^2 + s_a^2 s_b^2}$$

$$s_{indirect} = 0.0002$$

where a represents the coefficient on education in equation (a) and b denotes the coefficient on occupation in equation (b). As a result, the corresponding t-statistic for the indirect effect is:

$$t_{indirect} = \frac{\rho_1 - \delta_1}{s_{indirect}} = \frac{0.0891 - 0.0691}{0.0002} = \frac{0.0200}{0.0002} = 100.0$$

As the above finding fulfills Condition (3), it verifies the presence of an indirect effect of education on wages acting *through* occupation. Therefore, the above examination confirms the relationship between education and occupation in the wage equation as espoused in Figure 2, namely that occupation serves as a partial mediator in the influence of schooling on wages.

APPENDIX B

APPENDIX TABLE B1. Nested Logit Results, Displaced Blue-Collar Manufacturing Workers, Females, 2000-2004 DWS

	Participation Choice (Branch)		*Occupational Choice (Twig)*				
	Unemployed	*NILF*	*Professional, Management*	*Service*	*Sales*	*Clerical*	*Blue-Collar, Non-Man.*
Age							
20-24	0.113 (0.652)	1.518** (0.609)	-0.115 (0.956)	-0.035 (0.712)	0.425 (0.762)	0.746 (0.712)	0.728 (0.730)
25-34	0.409 (0.419)	0.655 (0.440)	-0.073 (0.635)	0.397 (0.445)	0.072 (0.576)	1.162** (0.464)	0.365 (0.587)
35-44	Base	Base	Base	Base	Base	Base	Base
45-54	0.358 (0.367)	-0.355 (0.410)	-0.355 (0.645)	-0.037 (0.447)	-1.154* (0.668)	-0.314 (0.520)	0.279 (0.563)
55-64	0.712 (0.514)	0.530 (0.522)	*	0.894 (0.543)	-0.064 (0.714)	-2.260** (1.135)	0.617 (0.716)
65 & up	0.492 (0.958)	1.799** (0.869)	*	*	*	*	*
Job Tenure	0.007 (0.021)	0.042** (0.020)	-0.012 (0.049)	-0.043* (0.026)	-0.002 (0.034)	0.022 (0.029)	-0.094** (0.048)
Race							
Black	-0.236 (0.394)	-0.775* (0.429)	-1.012 (0.926)	0.056 (0.428)	-0.117 (0.613)	-2.111*** (0.716)	-0.593 (0.667)
Other	-0.432 (0.477)	-0.957* (0.522)	*	-0.883 (0.688)	-1.338 (1.100)	*	-0.748 (0.825)
Married	-0.495* (0.281)	0.097 (0.296)	-0.842 (0.516)	-0.456 (0.323)	0.051 (0.437)	-0.019 (0.372)	-0.876** (0.425)
Children <18	0.112 (0.120)	-0.145 (0.137)	0.031 (0.209)	-0.133 (0.147)	-0.282 (0.211)	-0.313* (0.178)	-0.218 (0.196)
Union, Old Job	-0.142 (0.416)	-0.044 (0.430)	-1.934* (1.140)	0.012 (0.468)	-0.524 (0.733)	-0.445 (0.527)	0.079 (0.631)
US Citizen	0.903** (0.400)	0.762* (0.420)	0.461 (0.682)	0.199 (0.435)	0.554 (0.619)	0.681 (0.487)	0.122 (0.517)
Education							
Less than HS	-0.243 (0.308)	-0.485 (0.330)	-2.097* (1.089)	0.015 (0.358)	-0.837 (0.562)	-2.632*** (0.781)	-0.195 (0.459)
HS Diploma	Base	Base	Base	Base	Base	Base	Base
Some College	0.007 (0.446)	0.623 (0.434)	0.059 (0.639)	0.125 (0.480)	-0.061 (0.603)	0.087 (0.467)	-0.294 (0.649)
Vocational or Assoc. Deg.	0.360 (0.778)	-0.417 (0.977)	-0.308 (1.198)	0.978 (0.735)	0.355 (0.936)	0.987 (0.702)	0.399 (0.935)
College Deg.	1.486 (0.952)	1.268 (0.988)	2.418** (0.968)	*	*	-0.627 (1.285)	*

APPENDIX TABLE B1. Nested Logit Results, Displaced Blue-Collar Manufacturing Workers, Females, 2000-2004 DWS (cont.)

Region							
Northeast	0.103 (0.437)	-0.523 (0.460)	-0.044 (0.773)	0.132 (0.537)	-0.103 (0.715)	-0.988* (0.578)	-0.452 (0.632)
Midwest	-0.877* (0.478)	-0.232 (0.414)	0.089 (0.715)	0.332 (0.531)	-0.175 (0.713)	-0.495 (0.527)	-0.181 (0.608)
South	-0.233 (0.414)	-0.394 (0.422)	-0.859 (0.810)	0.197 (0.495)	-0.082 (0.671)	-1.136** (0.543)	-0.632 (0.581)
West	Base	Base	Base	Base	Base	Base	Base
City Status							
In City	0.244 (0.382)	0.403 (0.401)	-1.156 (0.871)	-0.521 (0.444)	-0.793 (0.659)	0.708 (0.489)	-0.484 (0.631)
Balance of City	-0.138 (0.336)	-0.171 (0.346)	-0.936 (0.583)	-0.691* (0.380)	-1.139** (0.563)	-0.550 (0.447)	-0.032 (0.482)
Non-Metro	Base	Base	Base	Base	Base	Base	Base
Other	-0.418 (0.428)	-0.484 (0.447)	-1.295* (0.760)	-1.368** (0.564)	-0.737 (0.594)	-0.025 (0.501)	-0.131 (0.585)
Notice of Layoff	-0.240 (0.284)	-0.160 (0.296)	0.184 (0.500)	-0.354 (0.329)	-0.407 (0.444)	-0.032 (0.369)	0.358 (0.412)
UI Exhaustee	-0.119 (0.315)	0.099 (0.324)	0.414 (0.568)	0.365 (0.349)	-0.572 (0.540)	0.495 (0.398)	-0.241 (0.498)
Inclusive Values	Em-ployed	1.223	Unem-ployed	0.5000	NILF	0.5000	
Observations	633						
Log-likelihood	-1029.0818						
LR chi2(169)	574.4094						
Prob > chi2	0.0000						

Note: Standard error in parentheses.

APPENDIX C

APPENDIX TABLE C1. Regression Analysis on ln(Hourly Wage), With Firm Controls, Setting OSHC=0 for All Non-Employed High School Seniors

Ln(wage)	*Same Occupational Category*	t_{sa}	q_{sa}
Race/Ethnicity			
Black	-0.045 (0.040)	-0.043 (0.040)	-0.048 (0.040)
Hispanic	-0.006 (0.050)	-0.006 (0.050)	-0.006 (0.050)
White / Other	Base	Base	Base
Region			
Northeast	0.080* (0.041)	0.081** (0.041)	0.078* (0.041)
North Central	0.067* (0.037)	0.065* (0.037)	0.064* (0.037)
South	Base	Base	Base
West	0.122*** (0.041)	0.121*** (0.041)	0.120*** (0.041)
MSA Status			
City	-0.014 (0.034)	-0.015 (0.034)	-0.013 (0.034)
Suburbs	Base	Base	Base
Other	-0.088** (0.034)	-0.089*** (0.034)	-0.086** (0.034)
Married at 20	0.029 (0.051)	0.028 (0.051)	0.029 (0.051)
Union Member at 20	0.169*** (0.046)	0.168*** (0.046)	0.167*** (0.046)
ASVAB pct * 100	0.0001 (0.0005)	0.0001 (0.0005)	0.0001 (0.0005)

APPENDIX TABLE C1. Regression Analysis on ln(Hourly Wage), With Firm Controls, Setting OSHC=0 for All Non-Employed High School Seniors (cont.)

Smoked Marijuana in HS	-0.033 (0.028)	-0.032 (0.028)	-0.033 (0.028)
Second Language at Home	-0.031 (0.053)	-0.033 (0.053)	-0.032 (0.053)
Worked in High School	0.062** (0.031)	0.022 (0.061)	0.026 (0.057)
OSHC	0.062 (0.046)	0.085 (0.085)	0.085 (0.084)
Worked at Same Firm	0.020 (0.054)	0.037 (0.051)	0.032 (0.054)
Occupation at age 20 (14 categories)	Yes	Yes	Yes
R-squared	0.2597	0.2586	0.2586
Observations	598	598	598

*Notes: Standard errors in parentheses. * - p<0.10; ** - p<0.05; *** - p<0.01.*

REFERENCES

Acemoglu, Daron, and Jorn-Steffen Pischke. 1998. "Why Do Firms Train? Theory and Evidence," *Quarterly Journal of Economics* 113, 79-119.

Acemoglu, Daron and Jorn-Steffen Pischke. 1999. "Beyond Becker: Training in Imperfect Labor Markets," *Economic Journal* 109, 112-42.

Addison, John T., and Pedro Portugal. 1989. "Job Displacement, Relative Wage Changes, and Duration of Unemployment," *Journal of Labor Economics* 7, 281-302.

Alsaker, Francoise D., and Flammer, August. 1999. *Time Use by Adolescents in an International Perspective: II. The Case of Necessary Activities.* Mahwah, N.J.: Erlbaum.

Altonji, Joseph G. 1995. "The Effects of High School Curriculum on Education and Labor Market Outcomes," *The Journal of Human Resources* 30, 409-38.

Anderson, Deborah, and David Shapiro. 1996. "Racial Differences in Access to High-Paying Jobs and the Wage Gap between Black and White Women," *Industrial and Labor Relations Review* 49, 273-86.

Arai, Mahmood. 2003. "Wages, Profits, and Capital Intensity: Evidence from Matched Worker-Firm Data," *Journal of Labor Economics* 21, 593-618.

Bailey, T., and Roger Waldinger. 1991. "Primary, Secondary, and Enclave Labor Markets: A Training Systems Approach," *American Sociological Review* 56, 432-45.

Baron, Reuben M., and David A. Kenny. 1986. "The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations," *Journal of Personality and Social Psychology* 51, 1173-82.

Becker, Gary S. 1962. "Investment in Human Capital: A Theoretical Analysis." *The Journal of Political Economy* 70(2), 9-49.

Becker, Gary S. 1993. *Human Capital.* National Bureau of Economic Research: The University of Chicago Press.

Belman, Dale and Heywood, John. 1991. "Sheepskin Effects in the Return to Education: An Examination of Women and Minorities," *Review of Economics and Statistics* 73, 720-24.

Belzil, Christian, and Hansen, Jorgen. 2002. "Unobserved Ability and the Return to Schooling." *Econometrica* 70, 2078-91.

Bishop, John. 1998. "Occupation-Specific Versus General Education and Training," *The Annals of the American Academy of Political and Social Science* 559, 24-38.

Bloch, Farrell E. and Sharon P. Smith. 1977. "Human Capital and Labor Market Employment," *The Journal of Human Resources* 12, 550-60.

Blaug, Mark. 1976. "The Empirical Status of Human Capital Theory: A Slightly Jaundiced Survey." *Journal of Economic Literature* 14, 827-55.

Borjas, George J. 1980. "The Relationship Between Wages and Weekly Hours of Work: The Role of Division Bias," *The Journal of Human Resources* 15, 409-23.

Bourguignon, Francois, Martin Fournier, and Marc Gurgand. 2007. "Selection Bias Corrections Based on the Multinomial Logit Model: Monte Carlo Comparisons," *Journal of Economic Surveys,* 21, 174-205.

Bowman, Mary Jean. 1974. "Learning and Earning in the Postschool Years," In *Review of Research in Education,* ed. Frank N. Kerlinger and John B. Carroll, 202-44. Itasca, Illinois: Peacock.

Bradbury, Katherine L. 2002. "Education and Wages in the 1980s and 1990s: Are All Groups Moving Up Together?" *New England Economic Review*, 19-46.

Bratsberg, Bernt, James F. Ragan, Jr., and Zafar M. Nasir. 2002. "The Effect of Naturalization on Wage Growth: A Panel Study of Young Male Immigrants," *Journal of Labor Economics* 20, 568-97.

Budd, John W. 2005. "Ideas versus Ideology: The Origins of Modern Labor Economics – Comment on Gallaway and Vedder," *Journal of Labor Research* 26, 177-80.

Cain, Glen. 1976. "The Challenge of Segmented Labor Market Theories to Orthodox Theory: A Survey." *Journal of Economic Literature* 14, 1215-57.

Card, David. 1998. "*The Causal Effect of Education on Earnings.*" Working Paper No. 2, Center for Labor Economics, University of California, Berkeley.

Carr, Rhoda V., James D. Wright, and Charles J. Brody. 1996. "Effects of High School Work Experience a Decade Later: Evidence from the National Longitudinal Survey," *Sociology of Education*, 69, 66-81.

Carrington, William J. 1993. "Wage Losses for Displaced Workers: Is It Really the Firm That Matters?" *The Journal of Human Resources* 28, 435-62.

Carrington, William J., Kristin McCue, and Brooks Pierce. 1996. "The Role of Employer/Employee Interactions in Labor Market Cycles: Evidence from the Self-Employed," *Journal of Labor Economics* 14, 571-602.

D'Amico, Ronald. 1984. "Does Employment During High School Impair Academic Progress?" *Sociology of Education,* 57, 152-164.

DeBeyer, J., and J.B. Knight 1989. "The Role of Occupation in the Determination of Wages." *Oxford Economic Papers* 41, 595-618.

DeSimone, Jeff. 2006. "Academic Performance and Part-Time Employment among High School Seniors," *Topics in Economic Analysis and Policy,* 6, 1466.

Dickens, W., and K. Lang. 1985. "A test of dual market theory," *American Economic Review* 75, 792-805.

Doeringer, Peter, and Michael Piore. 1971. *Internal Labor Markets and Manpower Analysis.* New York: Sharpe.

Dolton, Peter J., and Michael P. Kidd. 1998. "Job Changes, Occupational Mobility and Human Capital Acquisition: An Empirical Analysis," *Bulletin of Economic Research* 50, 265-95.

Dorman, Peter, and Paul Hagstrom. 1998. "Wage Compensation for Dangerous Work Revisited," *Industrial and Labor Relations Review* 52, 116-35.

Duncan, Greg J., and Bertil Holmlund. 1983. "Was Adam Smith Right After All? Another Test of the Theory on Compensating Wage Differentials," *Journal of Labor Economics* 1, 366-79.

Duncan, Otis Dudley. 1961. "Occupational Components of Educational Differences in Income," *Journal of the American Statistical Association* 56, 783-92.

Eckaus, Richard S. 1973. *Estimating the Returns to Education: A Disaggregated Approach.* Carnegie Foundation.

Evans, Davis S., and Linda S. Leighton. 1995. "Retrospective Bias in the Displaced Worker Surveys," *Journal of Human Resources* 30, 386-96.

Fairlie, Robert W., and Lori G. Kletzer. 1996. "Race and the Shifting Burden of Job Displacement from 1982 to 1993," *Monthly Labor Review* 119, 13-23.

Fallick, Bruce. 1996. "A Review of the Recent Empirical Literature on Displaced Workers," *Industrial and Labor Relations Review* 50, 5-16.

Farber, Henry. 2005. "What Do We Know About Job Loss in the United States? Evidence from the Displaced Worker Survey, 1984-2004," *FRB Chicago Economic Perspectives* 29, 13-28.

Farber, Henry. 1997. "The Changing Face of Job Loss in the United States, 1981-1995," *Brookings Papers on Economic Activity, Microeconomics,* 55-128.

Farber, Henry. 1993. "The Incidence and Costs of Job Loss, 1982-1991," *Brookings Papers on Economic Activity, Microeconomics*, 73-119.

Fogel, Walter. 1979. "Occupational Earnings: Market and Institutional Influences," *Industrial and Labor Relations Review* 33, 24-35.

Fox, Douglas A. 1994. "Displacement and Occupational Mobility: Evidence from the Displaced Worker Surveys," *Eastern Economic Journal* 20, 311-24.

Frazis, Harley. 2002. "Human Capital, Signaling, and the Pattern of Returns to Education," *Oxford Economic Papers* 54, 298-320.

Freeman, James A. and Barry T. Hirsch. 2001. "Do Returns to Human Capital Equalize Across Occupational Paths?" *Research in Labor Economics* 20, 217-42.

Fuchs, Victor R. 1982. "Self-Employment and Labor Force Participation of Older Males," *The Journal of Human Resources* 17, 339-57.

Fuligni, Andrew J., and Harold W. Stevenson. 1995. "Time Use and Mathematics Achievement among American, Chinese, and Japanese High School Students," *Child Development*, 66, 830-842.

Gera, Surendra, and Gilles Greiner. 1994. "Interindustry Wage Differentials and Efficiency Wages: Some Canadian Evidence," *The Canadian Journal of Economics* 27, 81-100.

Gibbs, Mike, Kathy Ierulli, and Eva M. Meyersson Milgrom. 2002. "Careers in Firm and Occupational Labor Markets," Mimeo., CDDRL, Stanford University.

Gill, Andrew M. 1988. "Choice of Employment Status and the Wages of Employees and the Self-Employed: Some Further Evidence," *Journal of Applied Econometrics* 3, 229-34.

Gill, Andrew M. 1994. "Incorporating the Causes of Occupational Differences in Studies of Racial Wage Differentials," *The Journal of Human Resources* 29, 20-41.

Goldstein, Jonathan P., Lloyd C. Irland, Jennifer A. Senick, and Eric W. Bassett. 2005. "The Intergenerational Supply of Loggers Under Conditions of Declining Economic Well-Being," *Industrial Relations* 44, 331-40.

Gottschalk, Peter T. 1978. "A Comparison of Marginal Productivity and Earnings by Occupation," *Industrial and Labor Relations Review* 31, 368-78.

Greene, William. 2002. *Econometric Analysis.* Fifth Edition. Upper Saddle River, N.J.:Prentice Hall.

Griliches, Zvi. 1977. "Estimating the Returns to Schooling: Some Econometric Problems." *Econometrica* 45, 1-22.

Groen, Jeffrey A. 2006. "Occupation-Specific Human Capital and Local Labor Markets," *Oxford Economic Papers* 58, 722-41.

Gyimah-Brempong, Kwabena, Rudy Fichtenbaum, and Gregory Willis. 1992. "The Effects of College Education on the Male-Female Wage Differential," *Southern Economic Journal* 58, 790-804.

Hagner, David. 2000. "Primary and Secondary Labor Markets: Implications for Vocational Rehabilitation," *Rehabilitation Counseling Bulletin* 44, 22-29.

Hauser, Robert M., and John Robert Warren. 1997. "Socioeconomic Indexes for Occupations: A Review, Update, and Critique," *Sociological Methodology* 27, 177-298.

Heckman, James. 1979. "Sample Selection Bias as a Specification Error," *Econometrica,* 47, 153-161.

Hellerstein, Judith K., David Neumark, and Kenneth R. Troske. 1999. "Wages, Productivity, and Worker Characteristics: Evidence from Plant-Level Production Functions and Wage Equations," *Journal of Labor Economics* 17, 409-46.

Hirsch, Barry T. 2005. "Why Do Part-Time Workers Earn Less? The Role of Worker and Job Skills," *Industrial and Labor Relations Review* 58, 525-51.

Hirsch, Barry T., and David A. Macpherson. 2004. "Wages, Sorting on Skill, and the Racial Composition of Jobs," *Journal of Labor Economics* 22, 189-210.

Hirsch, Barry T., and Edward J. Schumacher. 2004. "Match Bias in Wage Gap Estimates Due to Earnings Imputation," *Journal of Labor Economics* 22, 689-722.

Hotchkiss, Lawrence. 1993. "Effects of Training, Occupation, and Training-Occupation Match on Wage," *The Journal of Human Resources* 28, 482-96.

Hungerford, Thomas and Solon, Gary. 1987. "Sheepskin Effects in the Return to Education." *Review of Economics and Statistics* 69, 175-77.

Jacobson, Louis S., Robert LaLonde, and Daniel Sullivan. 2005. "Is Retraining Displaced Workers a Good Investment?" *FRB Chicago Economic Perspectives,* 47-66.

Jacobson, Louis S., Robert LaLonde, and Daniel Sullivan. 1993. *The Costs of Worker Dislocation.* Kalamazoo, Mich: W.E. Upjohn Institute for Employment Research.

Kambourov, Gueorgui, and Iourii Manovskii. 2004a. "Occupational Mobility and Wage Inequality," Working Paper; www.econ.upenn.edu/~manovski/papers/occ_mob_and_wage_ineq.pdf.

Kambourov, Gueorgui, and Iourii Manovskii. 2004b. "A Cautionary Note on Using (March) CPS Data to Study Worker Mobility," Working Paper; www.econ.upenn.edu/~manovski/papers/CautionaryNote.pdf.

Kambourov, Gueorgui, and Iourii Manovskii. 2005. "Occupational Specificity of Human Capital," Working Paper; www.econ.upenn.edu/~manovski/papers/occupation_specific_HC.pdf.

Kerr, Clark. 1977. "The Balkanization of Labor Markets." in *Labor Markets and Wage Determination,* ed. Clark Kerr. London: University of California Press.

Kleiner, Morris M. 2000. "Occupational Licensing," *The Journal of Economic Perspectives* 14, 189-202.

Kletzer, Lori G. 2001. *Job Loss from Imports: Measuring the Costs.* Washington, D.C.: Institute for International Economics.

Kletzer, Lori G. 1998. "Job Displacement," *The Journal of Economic Perspectives* 12, 115-36.

Kletzer, Lori G., and Robert W. Fairlie. 2003. "The Long-Term Costs of Job Displacement for Young Adult Workers," *Industrial and Labor Relations Review* 56, 682-98.

Knight, J.B. 1979. "Job Competition, Occupational Production Functions, and Filtering Down," *Oxford Economic Papers* 31, 187-204.

Kostiuk, Peter F. 1990. "Compensating Differentials for Shift Work," *The Journal of Political Economy* 98, 1054-75.

Kruse, William J. 1977. "An Empirical Study of Labor Market Segmentation: Comment." *Industrial and Labor Relations Review* 30, 508-23.

Kumar, Pradeep, and Mary Lou Coates. 1982. "Occupational Earnings, Compensating Differentials, and Human Capital: An Empirical Study," *The Canadian Journal of Economics*, 15, 442-57.

Langley, Paul C. 1978. "An Empirical Study of Labor Market Segmentation: Comment." *Industrial and Labor Relations Review* 32, 86-92.

Layard, Richard, and George Psacharopoulos. 1974. "The Screening Hypothesis and the Returns to Education," *The Journal of Political Economy* 82, 985-98.

Lazear, Edward P. 2003. "Firm-Specific Human Capital: A Skill-Weights Approach," NBER Working Paper No. W9679.

Lazear, Edward P. 1995. "A Jobs-Based Analysis of Labor Markets," *The American Economic Review* 85, in Papers and Proceedings of the Hundredth and Seventh Annual Meeting of the American Economic Association, Washington, D.C., January 6-8, 1995, 260-65.

Leonard, Thomas C. 2000. "The Very Idea of Applying Economics: The Modern Minimum-Wage Controversy and Its Antecedents," *History of Political Economy* 32, 117-44.

Light, Audrey. 1999. "High School Employment, High School Curriculum, and Post-School Wages," *Economics of Education Review,* 18, 291-309.

Lofstrom, Magnus. 2001. "A Comparison of the Human Capital and Signaling Models: The Case of the Self-Employed and the Increase in the Schooling Premium in the 1980s," *Research in Labor Economics* 20, 191-215.

MacDonald, C., and C. Sirianni. 1996. *Working in the Service Society.* Philadelphia: Temple University Press.

Macpherson, David A., and Barry T. Hirsch. 1995. "Wages and Gender Composition: Why Do Women's Jobs Pay Less?" *Journal of Labor Economics* 13, 426-71.

Marin, Alan, and George Psacharopoulos. 1982. "The Reward for Risk in the Labor Market: Evidence from the United Kingdom and a Reconciliation with Other Studies," *The Journal of Political Economy* 90, 827-53.

Marsh, Herbert W. 1991. "Employment During High School: Character Building or a Subversion of Academic Goals?" *Sociology of Education,* 64, 172-189.

Marsh, Herbert W., and Sabina Kleitman. 2005. "Consequences of Employment During High School: Character Building, Subversion of Academic Goals, or a Threshold?" *American Educational Research Journal,* 42, 331-369.

Mayhew, Anne. 1971. "Education, Occupation, and Earnings." *Industrial and Labor Relations Review* 24, 216-25.

Mazerolle, Maurice J., and Gangaram Singh. 2004. "Economic and Social Correlates of Re-Employment Following Job Displacement: Evidence from 21 Plant Closures in Ontario," *The American Journal of Economics and Sociology* 63, 717-30.

McNeal, Ralph B. 1997. "Are Students Being Pulled Out of High School? The Effect of Adolescent Employment on Dropping Out," *Sociology of Education,* 70, 206-220.

McNeal, Ralph B. 1995. "Extracurricular Activities and High School Dropouts," *Sociology of Education,* 68, 62-81.

Meyer, Robert H., and David A. Wise. 1982. "High School Preparation and Early Labor Force Experience," In *The Youth Labor Market Problem: Its Nature, Causes, and Consequences,* ed. Richard B. Freeman and David A. Wise, 277-341. Chicago: University of Chicago Press.

Michael, Robert T., and Nancy Brandon Tuma. 1984. "Youth Employment: Does Life Begin at 16?" *Journal of Labor Economics,* 2, 464-476.

Milgrom, E.M. 2004. "Boundaries of Internal Labor Markets: The Relative Importance of Firms and Occupations," Working Paper;
www.meyersson.com/boundary110804.pdf

Mincer, Jacob. 1958. "Investment in Human Capital and Personal Income Distribution," *Journal of Political Economy* 4, 281-302.

Mincer, Jacob. 1974. *Schooling, Experience, and Earnings.* National Bureau of Economic Research: Columbia University Press.

Mortimer, Jeylan T., and Michael D. Finch. 1986. "The Effects of Part-time Work on Adolescent Self-Concept and Achievement," In *Becoming a Worker,* edited by K. Borman and J. Reisman, 66-89. Norwood, N.J.: Ablex.

Mortimer, Jeylan T., Michael Finch, Michael Shanahan, and Seongryeol Ryu. 1992. "Work Experience, Mental Health, and Behavioral Adjustment in Adolescence," *Journal of Research on Adolescence,* 2, 25-57.

Nakeo, Keiko, and Judith Treas. 1994. "Updating Occupational Prestige and Socioeconomic Scores: How the New Measures Measure Up," *Sociological Methodology* 24, 1-72.

Neal, Derek. 1995. "Industry-Specific Human Capital: Evidence from Displaced Workers," *Journal of Labor Economics* 13, 653-77.

Oaxaca, Ronald. 1973. "Male-Female Wage Differentials in Urban Labor Markets," *International Economic Review* 14, 693-709.

Orazem, Peter F. and J. Peter Mattila. 1991. "Human Capital, Uncertain Wage Distributions, and Occupational and Educational Choices," *International Economic Review* 32, 103-22.

Osterman, Paul. 1975. "An Empirical Study of Labor Market Segmentation." *Industrial and Labor Relations Review* 28, 508-23.

Osterman, Paul. 1977. "An Empirical Study of Labor Market Segmentation: Reply." *Industrial and Labor Relations Review* 30, 221-24.

Parent, Daniel. 2000. "Industry-Specific Capital and the Wage Profile: Evidence from the National Longitudinal Survey of Youth and the Panel Study of Income Dynamics," *Journal of Labor Economics* 18, 306-23.

Picard, Pierre. 1993. *Wages and Unemployment.* Cambridge, UK: Cambridge University Press.

Poletaev, Maxim, and Chris Robinson. 2004. "Human Capital and Skill Specificity," University of Western Ontario Working Paper #2003-6.

Prasch, Robert E. "How is Labor Distinct from Broccoli? Some Unique Characteristics of Labor and Their Importance for Economic Analysis and Policy," in *The Institutionalist Tradition in Labor Economics,* ed. Dell P. Champlin and Janet T. Knoedler, 146-58. Armonk, N.Y.: Sharpe.

Quinn, Michael A. and Stephen Rubb. 2005. "The Importance of Education-Occupation Matching in Migration Decisions," *Demography* 42, 153-67.

Reder, Melvin. 1955. "The Theory of Occupational Wage Differentials," *American Economic Review* 45, 833-52.

Reiter, Ester. 1991. *Making Fast Food: From the Frying Pan into the Fryer.* Montreal: McGill-Queen's University Press.

Riley, John G. 1979. "Testing the Educational Screening Hypothesis," *The Journal of Political Economy* 87, *Part 2: Education and Income Distribution*, S227-S252.

Robst, John, and Kathleen Cuson-Graham. 1999. "The Effect of Uncertain Educational Requirements on Education and Wages," *Applied Economics* 31, 53-63.

Rothstein, Donna S. 2007. "High School Employment and Youths' Academic Achievement," *Journal of Human Resources*, 42, 194-213.

Ruhm, Christopher. 1997. "Is High School Employment Consumption or Investment?" *Journal of Labor Economics,* 15, 735-776.

Ruhm, Christopher. 1991. "Are Workers Permanently Scarred by Job Displacements?" *American Economic Review* 81, 319-23.

Rumberger, Russell W. 1987. "The Impact of Surplus Schooling on Productivity and Earnings," The Journal of Human Resources 22, 24-50.

Sakamoto, A., and M. Chen. 1991. "Inequality and attainment in a dual labor market," American Sociological Review 56, 295-308.

Schill, William J., Rosemarie McCartin, and Katrina Meyer. 1985. "Youth Employment: Its Relationship to Academic and Family Variables," Journal of Vocational Behavior, 26, 155-163.

Schmidt, Peter and Robert P. Strauss. 1975. "The Prediction of Occupation Using Multiple Logit Models," International Economic Review 16, 471-86.

Schoeni, Robert F., and Michael Dardia. 1996. "Wage Losses of Displaced Workers in the 1990s," RAND.

Schumacher, Edward J., and Barry T. Hirsch. 1997. "Compensating Differentials and Unmeasured Ability in the Labor Market for Nurses: Why Do Hospitals Pay More?" *Industrial and Labor Relations Review* 50, 557-79.

Schumann, Paul L., Dennis A. Ahlburg, and Christine Brown Mahoney. 1994. "The Effects of Human Capital and Job Characteristics on Pay," *The Journal of Human Resources* 29, *Special Issue: Women's Work, Wages, and Well-Being*, 481-503.

Schweitzer, Stuart O. 1971. "Occupational Choice, High School Graduation, and Investment in Human Capital," *The Journal of Human Resources* 6, 321-32.

Seitchik, Adam. 1991. "Who are Displaced Workers?" In *Job Displacement: Consequences and Implications for Policy, ed.* John T. Addison. Detroit: Wayne State University Press, 51-82.

Shaw, Kathryn L. 1984. "A Formulation of the Earnings Function Using the Concept of Occupational Investment," *The Journal of Human Resources* 19, 319-40.

Sicherman, Nachum, and Oded Galor. 1990. "A Theory of Career Mobility," *The Journal of Political Economy* 98, 169-92.

Siow, Aloysius. 1984. "Occupational Choice under Uncertainty," *Econometrica* 52, 631-46.

Smith, Adam. 1976. "An Inquiry into the Nature and Causes of the Wealth of Nations," in *The Works and Correspondence of Adam Smith,* ed. R.H. Campbell. London: Oxford University Press.

Soopramanien, Didier, and Geraint Johnes. 2001. "A New Look at Gender Effects in Participation and Occupation Choice," *Labour* 15, 415-43.

Spence, Michael. 1973. "Job Market Signaling," *The Quarterly Journal of Economics* 87, 355-74.

Stephenson, Stanley P. 1981. "In-School Labor Force Status and Post-School Wage Rates of Young Men," *Applied Economics,* 13, 279-302.

Stern, David, and Yoshifumi Nakata. 1989. "Characteristics of High School Students Paid Jobs and Employment Experience After Graduation," In *Adolescence and Work: Influences of Social Structures, Labor Markets, and Culture,* ed. D. Stern and D. Eichorn, 189-234. Hillsdale, N.J.: Erlbaum.

Stevens, Ann Huff. 1997. "Persistent Effects of Job Displacement: The Importance of Multiple Job Losses," *Journal of Labor Economics* 15, 165-88.

Sullivan, Paul. 2005a. "Empirical Evidence on Occupation and Industry Specific Human Capital," Working Paper;
http://www-personal.umich.edu/~paulsull/Sullivan_wagepaper_Oct2006.pdf.

Sullivan, Paul. 2005b. "A Dynamic Analysis of Educational Attainment, Occupational Choices, and Job Search," Working Paper;
http://www-personal.umich.edu/~paulsull/Sullivan_Occpaper_sept2006.pdf.

Taubman, Paul, and Michael L. Wachter. 1986."Segmented Labor Markets," *Handbook of Labor Economics, Vol. 2,* ed. Orley Ashenfelter and Richard Layard. Amsterdam: North Holland.

Taubman, Paul J., and Terence J. Wales. 1973. "Higher Education, Mental Ability, and Screening," *The Journal of Political Economy* 81, 28-55.

Thomas, Ward F., and Paul Ong. 2002. "Barriers to Rehiring of Displaced Workers: A Study of Aerospace Engineers in California," *Economic Development Quarterly* 16, 167-78.

Topel, Robert. 1991. "Specific Capital, Mobility, and Wages: Wages Rise With Job Seniority," *Journal of Political Economy* 99, 145-75.

Vedder, Richard, and Lowell Gallaway. 2005. "Ideas versus Ideology: The Origins of Modern Labor Economics – Reply to Budd," *Journal of Labor Research* 26, 181-82.

Weiss, Andrew. 1995. "Human Capital vs. Signaling Explanations of Wages," *The Journal of Economic Perspectives* 9, 133-54.

Weiss, Yoram. 1971. "Learning by Doing and Occupational Selection," *Journal of Economic Theory* 3, 189-98.

Wheeler, Christopher H. 2001. "Search, Sorting, and Urban Agglomeration," *Journal of Labor Economics* 19, 879-99.

Wooldridge, Jeffrey M. 2001. *Econometric Analysis of Cross Section and Panel Data.* Cambridge, Mass: The MIT Press.